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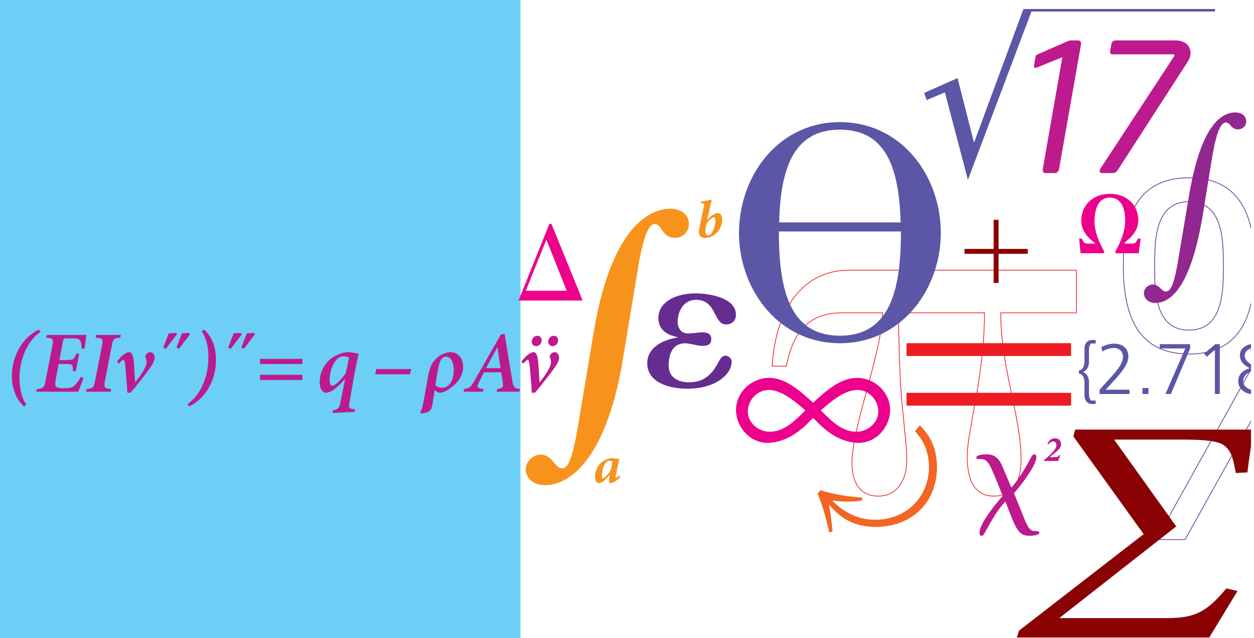
PhD Thesis



Simon Moritz Göhler
DCAMM Special Report No. S224
February 2017

DTU Mechanical Engineering
Department of Mechanical Engineering

Metric-driven Robust Design – Robustness Quantification of Complex Engineering Systems

PhD Thesis
Simon Moritz Göhler
February 2017

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Abstract

Variation is omnipresent - no two manufactured products are exactly the same or are used in exactly the same way and under the exact same conditions. To ensure quality and functionality for customer satisfaction, variation needs to be addressed in product development and production. In recent decades, the initiatives to deal with and address variation have moved more and more from quality control in production to the design and development phase. Rather than addressing the source of variation, Robust Design is applied as a strategy and paradigm to design products that are inherently insensitive to variation and function despite them. However, the ever-increasing complexity of products and engineering systems due to the integration of more functionality challenges engineers in designing robust products.

In this PhD thesis, this challenge of designing complex products and engineering systems to be robust to variation is addressed. More specifically, the robustness quantification and evaluation as an essential part of the design process to measure, monitor, select, prioritize and optimize for robustness has been investigated. A “metric-driven” approach enables an efficient and systematic Robust Design process.

Different angles on the quantification of robustness have been researched. A study of the landscape of Robust Design methods and tools revealed the mechanisms and coherences between the individual methods. An iterative Robust Design process was proposed based on the coherences and the associated activities of the engineers. It was also shown that the robustness evaluation plays a central role in the Robust Design process.

However, even though there is consensus among Robust Design practitioners and academics regarding the general concept of robustness as a paradigm and strategy to design products insensitive to variation, some ambiguities were still observed in the literature and in practice. A systematic literature study and analysis of robustness metrics led to the conclusion that four different notions of robustness exist: concept robustness, design robustness, function robustness and product robustness. For the latter, the complexity of the product has a large influence. This could be shown in a case study as well as in a model-based study which both revealed a reduction of robustness with an increased level of contradiction in the functions with larger/smaller-the-better requirements. This augments the work on Axiomatic Design by Suh, who proved this to be true for coupling and nominal-the-best requirements. To support the evaluation of the level of contradiction of a design, a method and metric, the Contradiction Index (CI), was developed.

Based on the insights gained throughout the research regarding the quantification of robustness, the VMF Tool was proposed to support a holistic and metric-driven Robust Design. By modeling and sensible decomposition of the (complex) product through relations of different degrees of fidelity, structural and functional robustness analyses have been incorporated. The VMF Tool supports the engineers to build a comprehensive functional understanding and enables efficient robustness quantification throughout the design process. Two case studies were conducted showing the merit and applicability of the tool, which has also been confirmed by qualitative feedback from participating engineers in the case companies.

Resumé (in Danish)

Variation er allestedsnærværende – ingen fremstillede produkter er helt ens, bruges præcist på den samme måde eller ved de præcist samme omstændigheder. For at sikre at kvaliteten og funktionaliteten tilfredsstiller kunden, er det nødvendigt at tage sig af variation i løbet af produktudviklingen og produktionen. I de seneste årtier har indsatsen for at adressere variation bevæget sig mere og mere fra kvalitetskontrol i produktionen til design- og udviklingsfasen. I stedet for at adressere variationskilderne anvendes Robust Design som en strategi eller et paradigme til at designe produkter, som er grundlæggende ufølsomme overfor variation og virker på trods af variation. Den stadigt stigende produkt- og systemkompleksitet, som skyldes forøgelsen af funktionalitet, udfordrer imidlertid ingeniører, når de skal designe robuste produkter.

I denne Ph.d.-afhandling adresseres udfordringen at designe komplekse produkter og systemer, så de bliver robuste overfor variation. Mere specifikt undersøges robusthedskvantificering og -evaluering for at måle, monitorere, vælge, prioritere, og optimere robusthed som en essentiel del af designprocessen. En ”metric-driven” tilgang tillader en effektiv og systematisk Robust Design-Proces.

Forskellige vinkler på robusthedskvantificeringen er blevet undersøgt. Et studie af landskabet af Robust Design-metoder og -værktøjer afslørede mekanismerne og fællestrækkende for de individuelle metoder. En iterativ Robust Design-Proces baseret på disse fællestræk og ingeniørernes tilhørende aktiviteter blev foreslået. Det blev også vist, at robusthedsevaluering spiller en central rolle i Robust Design-Processen.

Selvom der er konsensus iblandt akademikere og udøvere af Robust Design vedrørende det generelle robusthedsbegreb som et paradigme og en strategi til at designe produkter, der er ufølsomme over for variation, blev flertydigheder imidlertid stadig observeret i litteraturen og i praksis. Et systematisk litteraturstudie og analyse af robusthedsgrad førte til konklusionen, at fire forskellige opfattelser af robusthed eksisterer: konceptrobusthed, designrobusthed, funktionsrobusthed og produktrobusthed. Produktets kompleksitet har stor indflydelse på den sidstnævnte. Dette kunne vises i et casestudie og ligeså i et modelbaseret studie, som begge afslørede, at robustheden reduceres når ”jo-større/mindre-des-bedre”-krav til produktfunktioner modstrider hinanden i højere grad. Dette udvider Suhs arbejde med Axiomatisk Design, som beviste, at dette er sandt for koblinger og ”jo-tættere-på-nominelt-des-bedre”-krav. En metode og en måleenhed, Contradiction Index (CI), blev udviklet for at understøtte evalueringen af i hvor høj grad kravene modstrider hinanden i et design.

VMF-værktøjet blev foreslået baseret på den indsigt, der blev opnået gennem denne forskning vedrørende kvantificeringen af robusthed, således at en holistisk og “metric-driven” Robust Design-Proces kan understøttes. Strukturelle og funktionelle robusthedsanalyser er blevet inkorporeret ved modellering og fornuftig dekomposition af det (komplekse) produkt via sammenhænge med forskellige grader af nøjagtighed. VFM værktøjet understøtter ingeniørerne, så de kan opnå en omfattende funktionel forståelse og muliggør effektiv robusthedskvantificering igennem hele designprocessen. To casestudier blev gennemført, som viste værdien og anvendeligheden af værktøjet, som også blev bekræftet via kvalitativ feedback fra deltagende ingeniører i case-virksomhederne.

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Last but not least I would like to thank my family and especially my better half Susanne who gave me strength and supported me throughout the endeavor of doing this PhD project.

Simon Moritz Göhler
Kgs. Lyngby, February 2017

List of papers

Paper A
Mechanisms and coherences of robust design methodology: a robust design process proposal
Göhler, S.M.; Ebro, M. & Howard, T. J. (2016). In *Total Quality Management & Business Excellence*.

Paper B
Robustness Metrics: Consolidating the Multiple Approaches to Quantify Robustness
Göhler, S.M.; Eifler, T. & Howard, T. J. (2016). In *Journal of Mechanical Design.*

Paper C
The Contradiction Index: a new Metric combining System Complexity and Robustness for early Design Stages
Göhler, S.M. & Howard, T. J. (2015). In *ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. American Society of Mechanical Engineers.

Paper D
A model-based approach to associate complexity and robustness in engineering systems
Göhler, S.M.; Frey, D. D. & Howard, T. J. (2016). In *Research in Engineering Design*.

Paper E
The Translation between Functional Requirements and Design Parameters for Robust Design
Göhler, S.M.; Husung, S. & Howard, T. J. (2016).In *Procedia CIRP*.

Paper F
The Variation Management Framework (VMF) Tool for Robust Design
Göhler, S.M.; Mathiasen, M. R.; Nielsen, M. B.; Eifler, T. & Howard, T. J. (2017). Submitted to *Journal of Engineering Design.*

List of supplementary papers

Paper G
Design to Process Capabilities: challenges for the use of Process Capability Databases (PCDBs) in development
Eifler, T.; Göhler, S.M. & Howard T. J. (2014). In *25th Symposium Design for X*.

Paper H
A visual interface Diagram for mapping Functions in integrated Products
Ingerslev, M.; Jespersen, M. O.; Göhler, S. M. & Howard, T. J. (2015). In *Proceedings of the 20th International Conference on Engineering Design (ICED 15).*

Paper I
The Variation Management Framework (VMF): A Unifying Graphical Representation of Robust Design
Howard, T. J.; Eifler, T.; Pedersen, S. N.; Göhler, S. M.; Boorla, S. M. & Christensen, M. E. (2017). In *Quality Engineering.*

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1. Introduction

This chapter provides an introduction to this PhD research project. Starting with the description of the problems experienced in industry regarding the development of robust complex products, the motivation and relevance for the research are outlined. This is followed by the presentation of the current state of the art in Robust Design engineering which builds the foundation of the work at hand. The aims and objectives of this PhD project are then laid out and the research questions and initial hypotheses presented. The introduction concludes with the description of the DTU-Novo Nordisk Robust Design research project and the outline of this thesis.

1.1. Problem Description and Motivation for this Research

In 2013, the management consulting firm McKinsey estimated the cost of quality in the medical device industry to be between 17 and 26 billion dollar per year, equaling 12 to 18% of the industry's total revenue (1). A study by Mahmood & Kureshi (2) found that this value can be even higher and up to 40% of the total revenue in other industries. Variation is omnipresent and a major factor for reduced quality as well as an essential driver for cost, both in the form of prevention and appraisal cost but also costs related to internal and external failure (3). An example for the latter is the recall of 2.3 million cars by Toyota in conjunction with a variation sensitive gas pedal in 2010, costing several fatalities and about $3.1 billion in settlement and change costs (4). Another study by Reynolds (5) showed that the cost of rework related to variation "accounts for approximately 40% of the direct labor to build an airplane".

Robust Design, originally promoted by Japanese quality engineer Genichi Taguchi in the 1950s, is an acknowledged way to develop products that are inherently insensitive to variation. The merits are evident: robust systems behave more consistently benefitting the customer with improved reliability and durability. Robust systems, furthermore, allow more variation in production, resulting in higher yield rates and reduced demands on quality control, without adversely affecting the performance of the product (6). Addressing and managing variation from the initial conceptual design to production and use is essential for the quality and success of a product or engineering system.

With the emergence of systems engineering and multi-disciplinary development projects in recent decades, the complexity of products and engineering systems has steadily increased (7) and with it the difficulty to manage variation. Particularly in hardware and mechanical products the augmentation and integration of new and additional functionality as well as diversification are drivers for this trend and can be seen in all kinds of products and systems from insulin injection pens to smartphones, cars and airplanes (8). In addition to the increased complexity, further demands for performance, reliability and quality now exist to ensure customer satisfaction at any time. Moreover, companies face stronger competition in a globalized world which pushes the companies to shorter development times and reduced costs.

Nonetheless, the product needs to perform consistently and reliably despite variation and, to a certain extent, also under unintended use conditions. An efficient development process considering uncertainty and variation is essential to ensure quality and capture potential problems as early as possible. This is even more important, since the majority of costs in a product development project are committed to in the early development stages

(Figure 1). Efforts and activities to improve the quality of the design and to save costs therefore have a larger potential the earlier they are executed (9). The development process, methods and paradigms need to support the companies right from the first sketch until the design freeze, throughout engineering change management and even for product/module modification for new variants. The "right first time" philosophy, along with virtual validation and verification strategies has seen great progress, as seen in the automotive industry, now aiming to launch new vehicles in under 20 months (10).

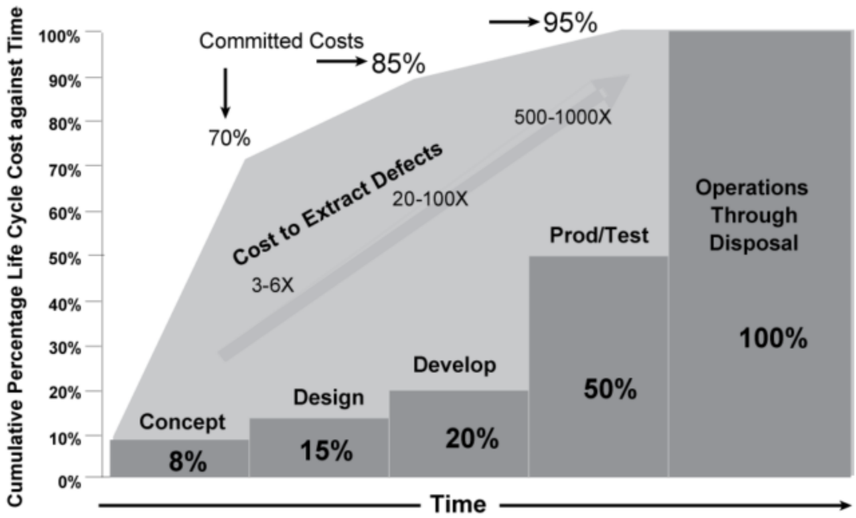


Figure 1: Committed life-cycle cost against time ((11) p. 15)

Yet many companies still experience major issues and costs during ramp up or while in production and use that are concerned with unwanted functional variation and non-conformance (12). Common practice is that problems related to variation and unpredictable performance are not recognized until very late in the development project leading to valuable resources being wasted – R&D/design engineers are re-assigned to "firefighting" activities, inspection and quality control is heightened and non-conforming parts/assemblies are scraped or re-worked. Failures of the product in the market can lead to even higher costs due to product recalls, customers compensation and loss of brand value, etc. (12).

A major issue is the lack of functional understanding and awareness when developing and designing products and systems (13) which is essential to cope with downstream uncertainty and variation. During the course of this PhD project this was confirmed by engineers at case companies as the following three examples show:

1. The chief engineer of a company developing medical devices mentioned that he had noticed that failed design milestones are oftentimes related to failing functionality even though structural indicators and kinematic constraint requirements were met.

2. An engineer responsible for the investigation of in-service failures of a large ship engine company reported that they experienced unexpected critical wear patterns. It turned out that geometrical and

use variations were not adequately taken into account during design due to a lack of functional understanding.

3. The lead engineer of another medical device company named the complexity of the product and lack of a functional overview as the main challenges to Robust Design.

The functional modeling and quantification of how robust a design solution is to perturbations and variation, as a measure for concept and design quality, is essential to objectively evaluate, monitor and improve functional performance. This is especially valuable during product development to avoid costly, late changes and/or failures in service.

1.2. State of the Art Robust Design

Robust Design is an acknowledged strategy to address aforementioned problems related to variation and has received more and more attention with diverse success with the implementation into companies' product development processes (14–17). In contrast to traditional quality initiatives that address variation in production, Robust Design aims to address variation already in the development phase. The paradigm shifts from addressing the source of variation to the propagation of the same which is an inherent characteristic of the design (18). It also follows that the focus changes from geometry to function.

In the Robust Design Methodology, different methods and strategies exist for the different design stages and information available. Traditional Robust Design methods as promoted by Taguchi exploit theories from the field of design of experiments, statistics and optimization to set the levels and tolerances of the design parameters for optimal robustness (6,18–22). The nature of the methods require, however, very mature models or prototypes for their application, which first become available considerably late in the design process. To address this limitation, other methods build upon a different approach. Robustness is therein fostered through the use of generic good design practice in the embodiment design stage (23,24) as also in part described by Pahl and Beitz (25). This includes among others constraint theory (26), kinematic design and design clarity (27), as well as other design features to damp or restrict variation propagation (23,28). Only little attention has been given to the investigation of complexity of the design solution as an indicator for robustness. Nam P. Suh formulated two design axioms claiming the transcendence of uncoupled designs with the least information content (29,30). Utilizing complexity as a predictor for robustness is especially valuable since it enables a consideration of robustness as early as in the conceptual design stage.

All in all, the different Robust Design efforts throughout the conceptual, embodiment and detailed design stages are not coherent and oftentimes uncoordinated following the maxim “the more robustness the better”. In complex products this is not always possible due to limited resources (31). Different approaches exist to manage variation (31–35). Often a key characteristic (KC) approach is utilized limiting the number of parameters that need to be modelled and controlled in design and production, respectively. The view on complexity also opens up the opportunity for a holistic evaluation of robustness which is the prerequisite for an efficient metric-driven Robust Design and variation management. Existing frameworks and tools often capitalize only on a fraction of the available information or have other limitations which can be summarized with the following points:

- Geometry-centric instead of function-driven variation management and Robust Design (Variation Risk Management (VRM) (31), tolerancing tools)
- Simplification to single functions instead of holistic systems perspective (Taguchi Method (18,19), Variation Mode and Effect Analysis (VMEA) (36,37), single-objective robustness optimization)
- Simplification to linear correlations between functions and parameters (Axiomatic Design (29), VRM (31), VMEA (36,37), other approaches to map products using stiffness matrices)
- Focus on EITHER structural (complexity related) OR functional, quantitative information (House of Quality (38), matrix-based approaches like DSM and MDM, multi-objective robustness optimization)

1.3.Aim and Objectives

The aim of this research was to support metric-driven Robust Design of complex products and engineering systems by providing a basis for the quantification of robustness throughout the development. The objective quantification of robustness lays the ground for metric-driven prioritization, monitoring, concept selection and optimization. Citing a common saying in quality engineering: **"You can only improve what you can measure"** (39)**.**

This PhD project researched complexity as a predictor for robustness continuing the work of Axiomatic Design by Nam P. Suh (29) and investigated into possibilities of a holistic, coherent, function-driven robustness quantification. The detailed objectives can be summarized as follows:

Objectives:

1. Clarification and evaluation of robustness quantification in the context of Robust Design activities
2. Investigation of the influence of product complexity on robustness
3. Exploration and derivation of a new metric to quantify or estimate robustness based on 2
4. Proposal of a tool to quantify robustness throughout the development of complex products and systems

1.4.Research Questions and Hypotheses

Following research questions (RQ) and hypotheses have been developed from the research objectives after an initial literature review and formulated to guide and structure the individual studies.

The first research question aims at the analysis of the current suite of Robust Design tools, methods, frameworks and processes – what tools and frameworks exist in academia and industry and what are the coherences between them based on their utilization by the development engineers in their daily design activities.

Research Question 1

a) *What Robust Design methods, frameworks and processes exist to analyze and synthesize robustness?*
b) *How can a coherent Robust Design process be prescribed?*

The answer to this research question shall lead to a clarification of the placement of robustness analysis and quantification in the product development process. This is especially interesting in terms of how a support for the development of robust complex engineering systems can be developed.

The general idea of a robust designs being insensitive to variation is widely acknowledged among academics and practitioners. However, there are different notions of robustness also reflected by the actual metrics used to quantify robustness in various situations like for example concept selection and robustness optimization. Research Question 2 addresses this ambiguity.

Research Question 2

What robustness indices and metrics and ways to derive these exist and what are their differences and limitations?

The development of robust complex products and engineering systems bears a lot of challenges also with respect to the quantification of robustness especially in earlier design stages. This leads to Research Question 3.

Research Question 3

What is the impact of complexity on robustness?

To cope with the complexity of the product or engineering system, an efficient decomposition is necessary leading to Research Question 4.

Research Question 4

How can functional requirements efficiently be decomposed to support robustness and tolerance management of complex products?

With the answers and conclusions from the first four research questions, a support shall be developed to improve metric-driven Robust Design of complex engineering products and systems leading to Research Question 5.

Research Question 5

How can a holistic and coherent metric-driven Robust Design be supported throughout the development of complex products and systems?

Besides the five research questions, two hypotheses have been formulated to guide the studies of this research project. Hypotheses are tentative answers to the overall research questions (40). The research then seeks to answer the research questions and to answer whether the hypotheses can be accepted or rejected.

Hypotheses

A) The complexity of an engineering system has a significant influence on its conceptual robustness against variation.
B) A holistic and quantitative approach based on robustness AND complexity considerations can improve the functional understanding and support metric-driven Robust Design of complex engineering systems.

Table 1 gives an overview of in which of the appended scientific papers the individual research questions are addressed and answered.

Table 1: Overview of which Research Questions are answered in which paper

	Paper A	Paper B	Paper C	Paper D	Paper E	Paper F
RQ1	X					
RQ2		X				
RQ3			X	X		
RQ4					X	
RQ5						X

1.5.Novo Nordisk - DTU Robust Design Program

This PhD research project is part of the Novo Nordisk – DTU Robust Design Program which was established in 2013 to foster a problem-driven research and education in the field of Robust Design and variation management. It consists of three PhD projects with research in the three main research areas. Figure 2 shows the 3 PhD work packages (WP) in the Variation Management Framework (VMF) (32), which represents the mapping and visualization of how variation in the customer, functional, physical or production domain gets propagated to the respective other domains and either dampened or amplified (41). This visualization has proven to be very useful in describing the different levers and possibilities of Robust Design (32). The individual projects are summarized in the following.

WP1: Work package 1 deals with the customer domain of variation, which describes the relation between the perceived quality (Q) by the customer to the functional requirements (FR) of the product. The estimation and modeling of the quality associated with functional variation from the nominal constitute the core of this work package.

WP2: The research presented in this PhD thesis is related to the second work package investigating robustness in the functional domain. It addresses the propagation of variation between functional requirements (FR) and design parameters. Robustness and complexity analyses are combined to support the development of complex products and systems to be robust against variation.

WP3: The research project in work package 3 seeks to adapt the Robust Design paradigm to the production domain and to utilize the information generated from the various analyses in product design. The goal is to support variation management in production by adjustment and optimization of the processes based on the insights from the development of the product.

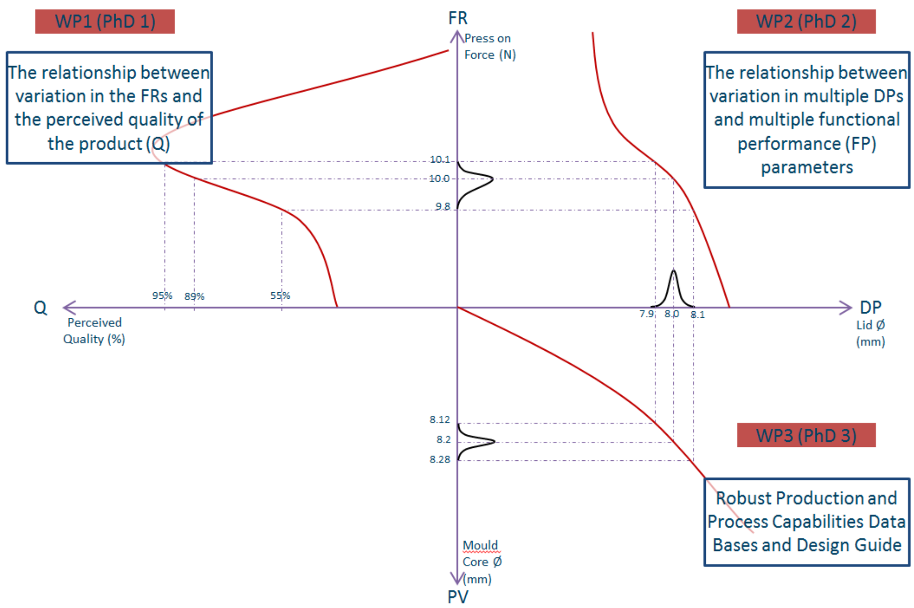


Figure 2: Mapping of variation through the customer, design and production domain (42)

Figure 3 shows the impact model (methodology adapted from Blessing and Chakrabarti (40)) for Robust Design. It depicts in a simplified manner how the process, design and perceptual sensitivity influence the propagation of variation and connects this quality characteristic to measurable financial metrics resulting in a “Profit” for a developing and producing company. The areas of research and contribution of this PhD projects are highlighted with red arrows and red boxed.

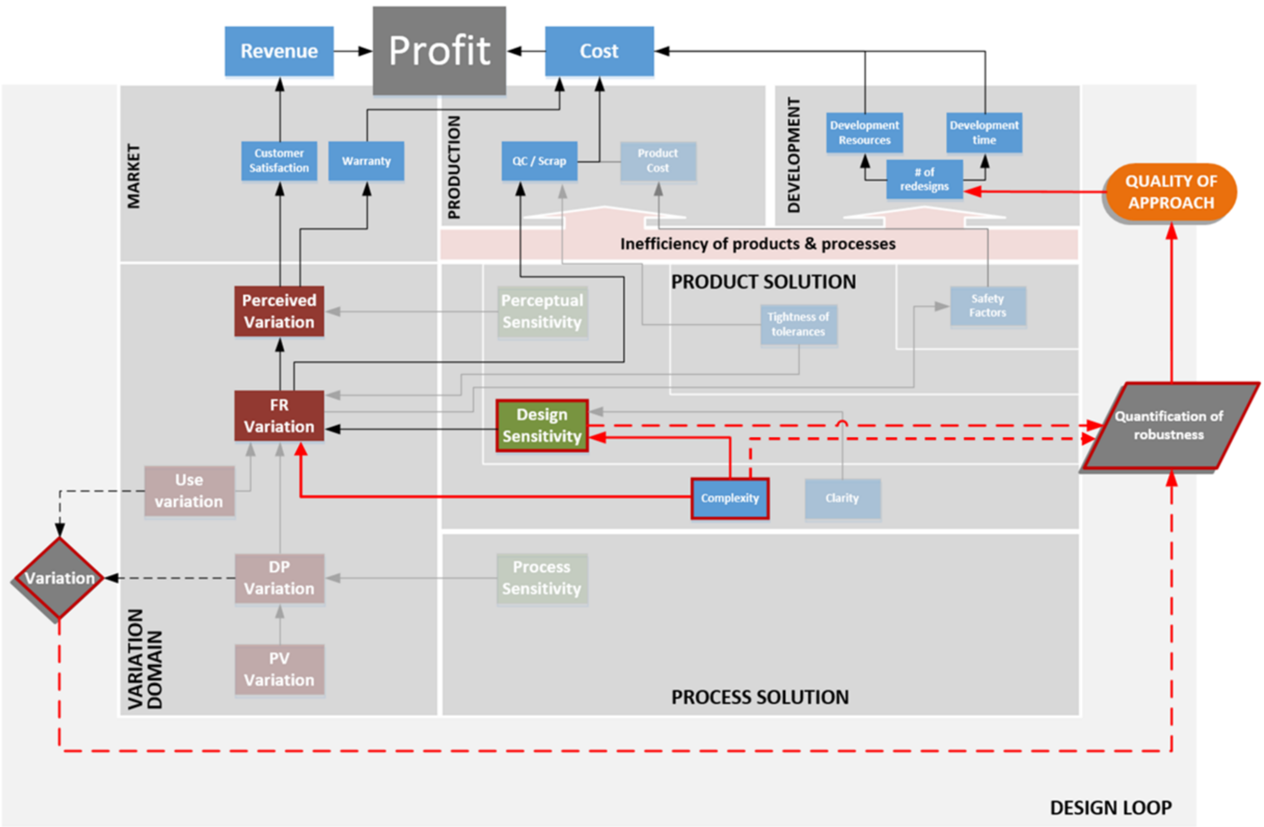


Figure 3: Impact model for Robust Design

1.6.Outline of Thesis

This PhD project and the thesis at hand is so-called "paper-based". As opposed to classic conventional monograph dissertations, a paper-based thesis has its focus on scientific publications over the span of the 3-year research project. The thesis itself is therefore only a short description and summary of the work and contribution of the research. The details of the single studies can be found in the attached journal and conference articles. All of those have been peer-reviewed and have undergone a rigorous evaluation by a specialist committee before publication (note that Paper F has been in review at the time of the submission of this thesis). In that way, the quality and also acceptance of the work by the scientific community is ensured. The thesis is organized as follows.

This introduction is followed by chapter 2, the "Research Approach" for this PhD project, summarizing the methodology assuring a rigorous and scientific conduction of the research.

Chapter 3, the "Theoretical basis", presents the established knowledge and theories that are essential for this research and which this work is built upon.

Chapter 4, “Results and Discussion”, summarizes and discusses the results of the different studies of this PhD project. The chapter closes with an evaluation of the PhD research as a whole.

The thesis concludes with Chapter 5, the “Conclusion”, which entails a reflection on the research project, its academic and industrial contributions as well as its impact and value. Finally, suggestions for further research are given.

2. Research Approach

This chapter describes the scientific approach to this research project. It entails the overall research methodology, methods and activities as well as a description of the strategies to verify and validate the outcomes of the research but also the research itself. The goal is to present the approach to assure the scientific rigor of this work. The chapter is concluded with the actual research plan and overview with the stages, studies and methods.

This research was conducted in the context of product development and engineering design. The study of natural systems and artificial systems is inherently different and needs different approaches and methodologies (43). According to van Aken (44) a differentiation can be made between explanatory science and design science. Explanatory science aims at describing causal dependencies in nature, whereas design science is more pragmatic and solution-oriented. Other researchers like Kothari et al. (45) talk about Basic research as opposed to Applied research (see Table 2) meaning similar things. The notion of relevance is crucial in design science i.e. applied research. One of the main goals of this research project is the applicability in real-world problems. The main focus is on mechanical design in product development.

Table 2: Differences between basic and applied research (45)

Basic research	Applied research
Seeks generalization	Studies individual or specific cases without the objective to generalize
Aims at basic processes	Aims at any variable which makes the desired difference
Attempts to explain why things happen	Tries to say how things can be changed
Tries to get all the facts	Tries to correct the facts which are problematic
Reports in technical language of the topic	Reports in common language

2.1. Research Methodology

The overall guiding stars for this PhD project were the Research Questions and Hypotheses that have been laid out in the previous chapter. The goal of this thesis was to answer the questions and whether the hypotheses can be accepted or rejected. The proper formulation of the research questions and hypotheses was an essential portion of the research methodology.

The work described in this thesis has elements of explanatory science but is mainly oriented towards design science and applied product development. The research was influenced by the research methodologies described by Jørgensen (46) as well as the one proposed by Blessing and Chakrabarti (40), which are common in design science. These methodologies were chosen due to the nature of the research project being quantitative and in design science.

2.1.1. Problem-based, Theory-based (PbTb) research approach

The PbTb research approach was proposed by Jørgensen (46) and essentially builds upon two ways to conduct research. As illustrated in Figure 4, research can have its origin in a problem statement but also in an existing theory or hypothesis that needs to be proven or disproven. Both are valid motivations to start a research project. However, the ways of approaching the research are different. In the case of a problem-based research, an analysis of the problem is required to find patterns and causalities. This can involve conducting experiments, simulations or other empirical studies. Building on the diagnosis for the problem, solutions can be developed and evaluated to finally arrive at new scientific knowledge. On the other hand, in a theory-based research approach, the starting point is the synthesis from the theory. Exploiting patterns leads to a model that then again is tested against the reality. The novel scientific contribution lies within a valid and useful model. The results from either approach - from the problem-based as well as the theory-based approach - might need further development and an implementation to industry to generate practical value. In practice both paradigms are used in research. New theories can be generated while working on a problem, but also new problems can be discovered while working on a theory.

This framework was seen relevant, because it reflects not only the design science part but can also be used to address the explanatory part of this research project.

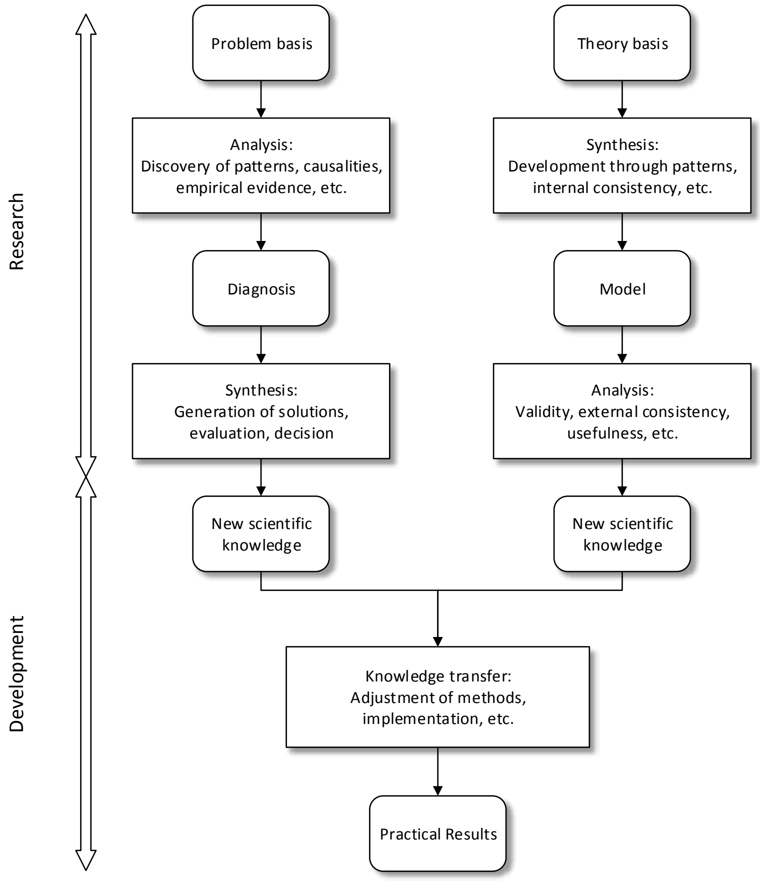


Figure 4: Design research model: Problem-based, Theory-based research approach (after Jørgensen (46))

2.1.2. Design Research Methodology (DRM)

Research in engineering design is often in the realm of applied research as discussed in the outline of this chapter where results can be difficult to quantify. Blessing and Chakrabarti (40) developed DRM to structure the research in this field to have a consistent and coherent methodology and framework for the formulation, execution and evaluation of the project. **Figure 5** shows the different stages of DRM, the basic means and the main outcomes. After an initial Research Clarification, descriptive and prescriptive studies are altered to generate knowledge, build theories and models to then again test those. The goal is to find and develop means to support engineering designers in their work. A more detailed description of the stages will be laid out in the following.

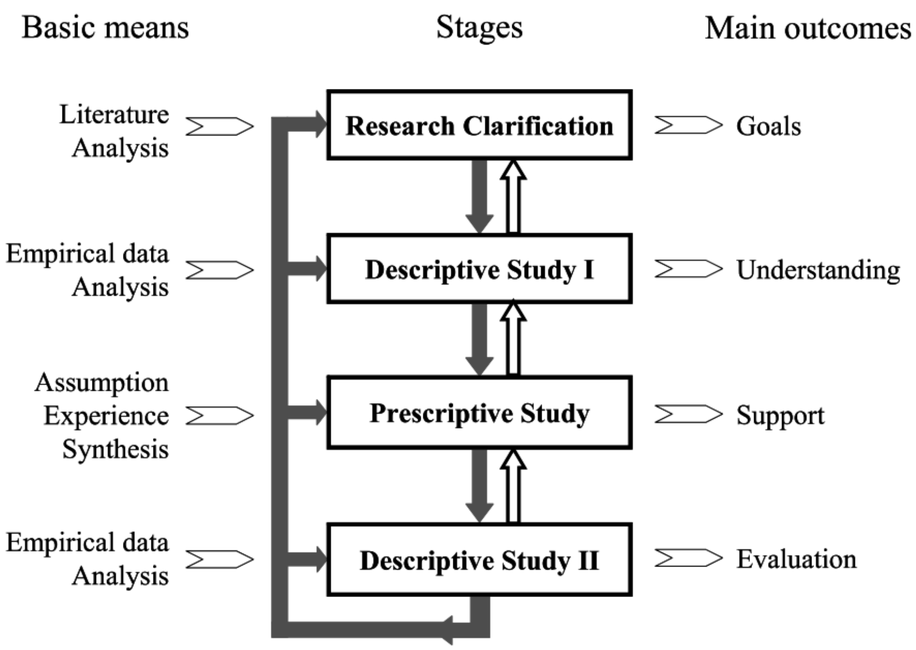


Figure 5: DRM framework redrawn from (40)

Stage 1: Research Clarification (RC)

The Research Clarification stage is the initial stage of the research project and lays the grounds and scope for the actual research. It is important on the one hand to get to know the field to an extent where “white-spots” and gaps in knowledge become evident but also on the other hand to delimit the research. Experience shows that especially in design research, this is a critical stage due to the sheer endless opportunities and spins the research could take and to an extent will take anyway. Generally, literature analyses are used in this stage with the outcome of clearly defined goals that are challenging but realistic and, when achieved, give value to research and society. An overall research plan should emerge including the research questions and hypotheses as well as the expected contribution and potential success criteria.

Stage 2: Descriptive Study I (DS I)

The Descriptive Study I builds upon the Research Clarification and seeks to explore, describe and explain the design phenomena in focus. Empirical studies, but also deeper investigations and analyses, are the basic means. The studies can either be theory- or data-driven and be of quantitative ("degree to which phenomena occur") or qualitative ("nature of phenomena") nature. As main outcome, this stage delivers a thorough understanding of the problem, its influencing factors and causes. This lays the basis and gives the insights for an effective development of a support and how the support can be evaluated.

Stage 3: Prescriptive Study (PS)

Based on the knowledge and understanding gained in DS I, new solutions or other support are developed addressing the identified key factors to solve the problem and improve the current situation. Common means in this stage are assumption, experience and synthesis. The proposal of new approaches or methods as support is the main outcome. Furthermore, a first evaluation of the support in terms of functionality and consistency is required. Also, success criteria and measureable success criteria should be determined to be able to fully evaluate the impact of the support.

Stage 4: Descriptive Study II (DS II)

The aim of the Descriptive Study II is to evaluate the support. It answers the question, whether the support addresses the key factors and has the intended impact on the success criteria. The means are the same as for DS I and include empirical studies and analyses. Based on the results and the experiences made during the test, potential necessary improvements and alterations to the support itself or to how it is implemented and used are put forth. Follow up studies might be necessary to conduct the final validation and verification of the support.

2.2.Research Methods

Depending on the research field and the research question to be answered, different research methods exist. The nature of research studies is usually categorized as exploratory, explanatory (causal inquiries) or descriptive (47). A further distinction can be made between qualitative and quantitative methods to describe different shades of a phenomenon. A short overview over relevant research methods and activities for this PhD project are given in the following.

Archival Analyses

The analysis of available material – in the context of product development and engineering design for example drawings, models, change notes, simulation and experiment data, etc. – to explore and describe a phenomenon yields valuable information to build or test theories, models or hypotheses.

Case studies

In the realm of applied research (design research) as previously discussed in this chapter, case studies build an essential link to the real-world investigating phenomena empirically. Case studies are often "used for exploratory research or for pre-testing some research hypotheses" (40). They are the "preferred method when the investigator has little control over events and the focus is on a contemporary phenomenon" (47). Complex phenomena can be investigated from a holistic standpoint within a real-life context.

Experiments

In classical natural science like physics and chemistry, experiments constitute the standard method to do research. But also in other fields, experiments that are of physical nature or in the form of computer simulations are a common way to test hypotheses and models.

(Systematic) literature reviews

The review of the literature serves several purposes. On the one hand, it is an indispensable tool to establish a knowledge base that enables the researcher to make a contribution in the first place but also to set the research into perspective to the work and knowledge of the rest of the research community. On the other hand, literature reviews can yield new insights and trends that are not obvious from the single contributions. Executed in a systematic and therefore reproducible manner with an aprioristically defined protocol furthermore ensures the completeness, rigor and credibility of the study (48).

Survey questionnaires

Surveys are a method to capture "thoughts, beliefs, opinions, reasons etc." (40) and allow for exploratory and descriptive studies but also for feedback and evaluation studies. Questions can be formulated in a closed (multiple choice) or open form. There are some challenges with questionnaires such as preventing biases, asking a representative group of people etc. that need to be accounted for to ensure reliable and meaningful results. Furthermore, there are high demands regarding the formulation of the questions for understandability to secure the least room for interpretation (49).

2.3. Verification and validation of the results of this research

The validation and verification (V&V) of the results are an essential part of the reflection on the research. In the following, different models and argumentations on how the V&V of the results of this research have been conducted are discussed.

The use of the terms "Validation" and "Verification" is very inconsistent across different research fields and disciplines and can be used in reversed ways. For this research, the notion from system modelling (50) is taken.

1. Verification refers to the internal consistency
2. Validation refers to the justification of knowledge claims

In systems modelling as well as in classical natural science (Basic research) a “formal, rigorous and quantitative validation” is required (50,51). A distinction can be made between causal (theory-like) models and non-causal (statistical/correlational) models which again demand different ways of verification and validation (50). However, in the field of design research a quantitative validation can be challenging and is not always possible due to for example qualitative output or little empirical evidence. Still, the internal consistency and value (usefulness) of the research/support need to be shown. There are different verification and validation strategies that have been proposed in the field of engineering design that address this difficulty.

One of them is the “Validation square” introduced by Pedersen et al. (51). This methodology divides the V&V process into four parts (Figure 6).

1. Theoretical structural validity: is the general theory behind the support accepted and is the support consistent?
2. Empirical structural validity: appropriateness of example case to show that support is useful
3. Empirical performance validity: measuring the usefulness of the results from applying the support
4. Theoretical performance validity: evaluation of the generalizability of the usefulness of the support from the empirical case study

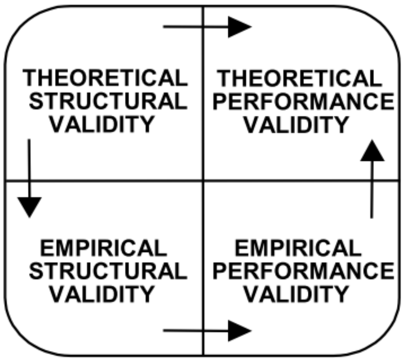


Figure 6: The Validation Square redrawn from Pedersen et al. (51)

A similar way of validating the value of a support is described in Blessing’s and Chakrabarti’s Design Research Methodology (DRM) (40). A so called impact model is established in the beginning of the project and measurable success criteria defined. Those success criteria are evaluated before and after a support has been introduced to determine the impact and value of the support.

Another method is deductive reasoning why a method or support is inevitably useful and valuable. Buur (52) proposed to have a logical verification and a validation by acceptance:

Logical verification

- Consistency: there are no internal conflicts between individual elements (e.g. axioms) of the theory
- Completeness: all relevant phenomena observed previously can be explained or rejected by the theory

- Cases (i.e. particular design projects) and specific design problems can be explained by means of the theory

Validation by acceptance (*has been changed from verification to maintain consistency for this thesis)*

- Statements of the theory (axioms, theorems) are acceptable to experienced designers
- Models and methods derived from the theory are acceptable to experienced designers

2.4. Research Design

The methodologies introduced in the previous sections give the basis for the research design and serve for a structured approach. Nevertheless, research is not always linear, sequential and plannable as described in those methodologies. Opportunistic research guided by the methodology can be the more realistic and also more fruitful research. Opportunities arrive through case studies, projects with companies, master's projects, other assignments and simply through the development of interest finding the right niche for the research.

The different methods and V&V strategies were used to conduct and evaluate the different studies of this PhD project. The remainder of this section illustrates the line of argument of this research, summarizes how the studies were conducted as well as the general time plan including publications.

2.4.1. Research line of argument

As described in the introduction chapter of this thesis, the aim of this research project is to shed light on the robustness quantification and variation management of complex mechanical systems and to develop a support for people involved in the development of such systems to evaluate and monitor the level of robustness throughout the development process. Figure 7 visualizes the line of argument for this research. The starting point is the current practice and the establishing of a frame of reference for further investigations. The term "quantification" implies the use of metrics. The second part of the research therefore deals with metrics from quantitative as well as qualitative models supporting the general assessment of robustness. Lastly, a supporting tool incorporating the gained knowledge is to be developed and tested.

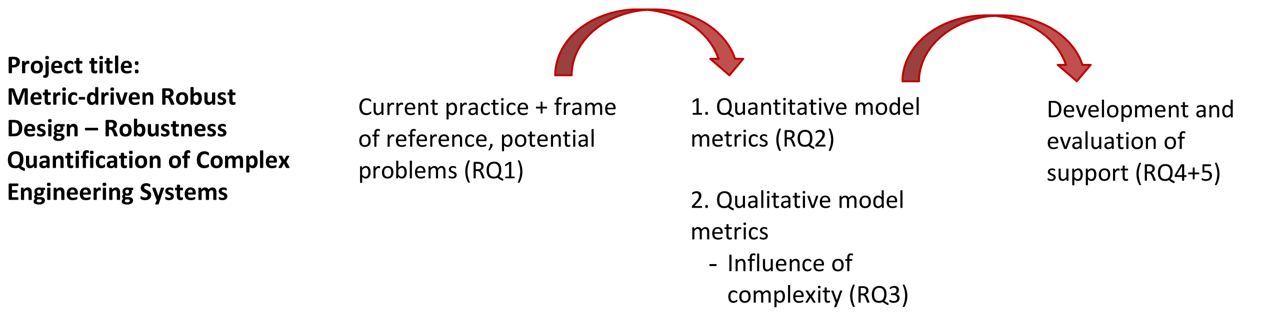


Figure 7: Research line of argument

2.4.2. Studies and research plan

For this research project, several separate studies were conducted to answer the research questions. New insights but also new problems arose more or less directly from the studies influencing the succeeding studies.

Figure 8 shows the research plan - the general timing of the different stages and studies concluding with a scientific publication in a journal or conference proceedings. The overview, furthermore, includes the associated research questions.

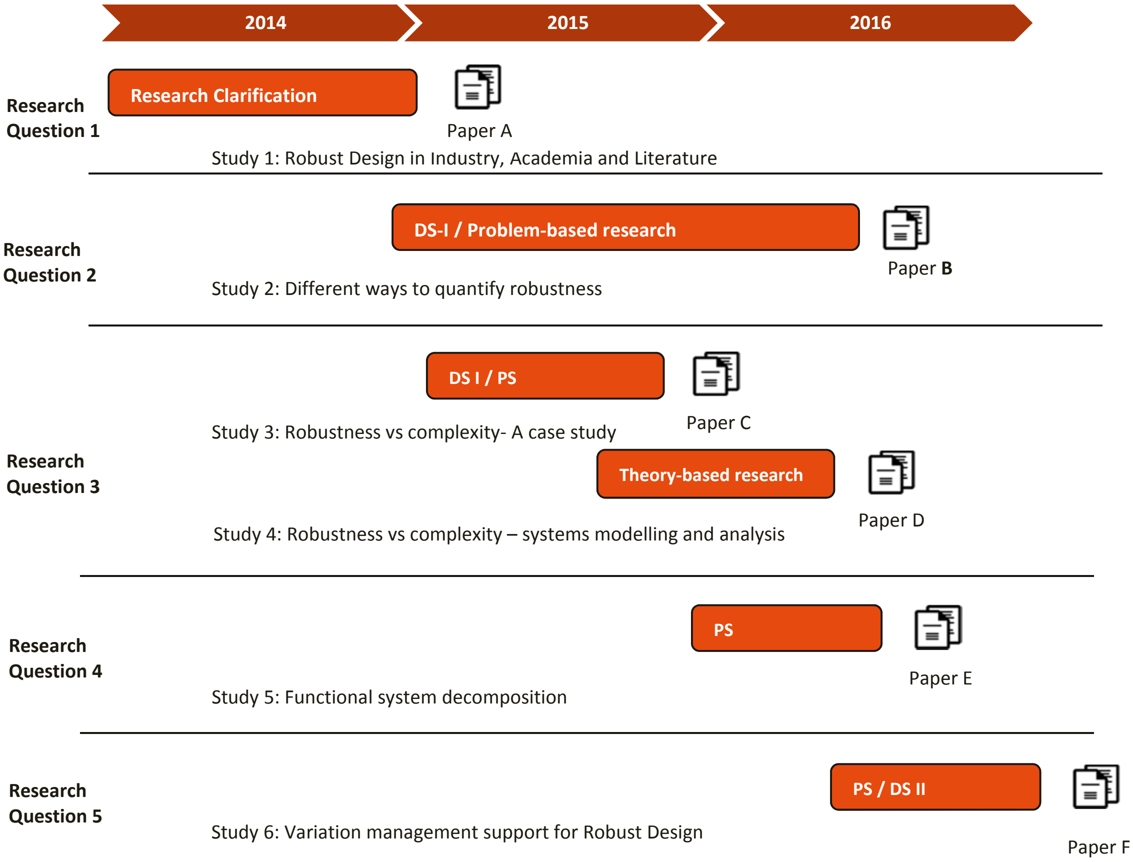


Figure 8: Research Plan

Study 1:

To create a frame of reference to place the efforts of evaluating and quantifying robustness in the greater picture of Robust Design a "Research Clarification" stage was conducted as the first study following the DRM methodology by Blessing and Chakrabarti (40). This study was influenced by the observation of the product development process at Novo Nordisk device R&D who have been a generous sponsor but also case company for this research. Tools and methods commonly associated with Robust Design in industry and academia were collected and reviewed to find mechanisms and coherences and to be able to set the "robustness evaluation" activity into context.

- **Stage**: Research Clarification
- **Methods**: Literature review, archival analyses (industry Robust Design toolboxes, feedback from academic workshops)

- **V&V**: Logical verification / deductive reasoning and validation by acceptance

Study 2:

While analyzing the different tools to evaluate robustness in study 1, it became clear that there is no commonly accepted metric to quantify robustness. A consolidation of the term robustness and an overview over the different metrics was necessary and was addressed by this study.

- **Stage**: DS-I / Problem-based research
- **Methods**: Systematic literature review
- **V&V**: Deductive reasoning

Study 3:

Industrial projects revealed that there was a need to take the functional complexity of products into consideration when evaluating the robustness. Study 3 was a case study analyzing the complexity and robustness of one of Novo Nordisk's insulin injection devices to get an idea about the hypothesized influence of complexity on robustness.

- **Stage**: DS-I / Problem-based research
- **Methods**: Case study, archival analysis
- **V&V**: Validation Square, Correlational model

Study 4:

The modelling of complex systems in study 4 was conducted to investigate the level of generalizability of the findings from study 3.

- **Stage**: Theory-based research
- **Methods**: Numerical systems modelling
- **V&V**: Correlational model, logical verification and validation by acceptance

Study 5:

A support tool to help developers of complex systems managing robustness and variation requires a model to structure and decompose the system. The goal of this study was to prescribe a model to achieve a comprehensive functional mapping of a complex system.

- **Stage**: Prescriptive study
- **Methods**: Literature review, deductive reasoning
- **V&V**: Logical verification, deductive reasoning and validation by acceptance

Study 6:

In this study, a tool was developed based on the research results from studies 1 to 5 to capture, process and present structural as well as functional information to support holistic robustness quantification and variation management. The tool was tested and its usefulness and applicability evaluated with two case studies.

- **Stage**: PS, DS-II
- **Methods**: Tool development and case studies
- **V&V**: Deductive reasoning, experiments, surveys

2.5. Other influences on the research

Experience and the sharing of knowledge among colleagues and fellow researchers significantly influence the reasoning and interpretation of results as well as the direction of the research project itself. Also, assignments and courses apart from the actual research have their impact. Different factors influenced me as the researcher in this project.

- Experience as a practitioner of Robust Design in the aviation industry
- Consultancy work in the realm of reliability engineering
- Education as Lean Six Sigma Black Belt
- Research stay at the Massachusetts Institute of Technology
- Project work at Novo Nordisk
- Visits of the engineering consultancies Cooper Perkins and Dragon Innovation
- Supervision of Master's projects with various companies
- Attendance and presentation at the Design 14, ASME 15 and CIRP CAT 16 conferences

3. Theoretical Basis

In the following chapter, the underlying theoretical basis for this research project will be described. The state of the art and most relevant theories and methods for this research will be presented. The aim is to assist the reader in understanding the contribution and relevance of the research and the individual scientific articles that are contained as well as position the results in the body of existing knowledge. Starting with the description of generic product development processes, the chapter continues with theory and definition of Robust Design and the frameworks related to it. The chapter concludes with the introduction of complexity in engineering systems and the basics in numerical model building.
Note that the theoretical basis will only be described to the extent necessary to understand and follow the research conducted in this PhD project. For further and more detailed information the reader is referred to the given references.

3.1. Product Development Processes

This research lies in the domain of product development and engineering design. To be able to place the work and the contribution of it in its context, common product development processes will be discussed in the following. Process models are used in academia and industry to describe and prescribe how to approach product development systematically to ensure a most efficient and effective execution of the task. The utilization of a product development process depends on the nature, complexity, novelty and criticality of a product or system that is to be developed. Most common are linear models prescribing a sequential flow of tasks and stages from an initial idea for a product to the production of it. However, it is widely acknowledged that product development is not a linear but rather an iterative process (53). Most developing companies use linear process models due to their capability to house stage gates to manage, plan and control the development efforts (54). Various linear process models have been proposed. Among those are the models by Pahl and Beitz (25), Ulrich and Eppinger (55), Andreasen and Hein (56) as well as Hubka and Eder (57). A comprehensive list of engineering design process models can be found in Howard et al. (54). The mentioned linear models have a common structure of the process entailing a concept stage, an embodiment stage and a detailed design stage. Figure 9 shows exemplarily the process model by Pahl and Beitz. The Systems Engineering approach takes a step back and decomposes the development of a system to the development of sub-systems down to components. The V-model is often used additionally to a stage gate model to organize integrational tasks and to link validation and verification on the different levels to their associated requirements (11,58). Figure 10 illustrates the V-model. Time and maturity advances from left to right.

Robust Design is not a development process itself but merely an approach and methodology to ensure product quality alongside the generic product development process. Generic processes are therefore of relevance to place Robust Design activities like the quantification of robustness as researched in this PhD project relative to all other activities. A generic evaluation of a design solution can already be found in the displayed process models. The quantification of quality characteristics like robustness is essential for the improvement, optimization, benchmarking and verification of the design solution and to foster metric-driven decision making utilizing also the ever emerging power of Computer-aided Engineering (CAE).

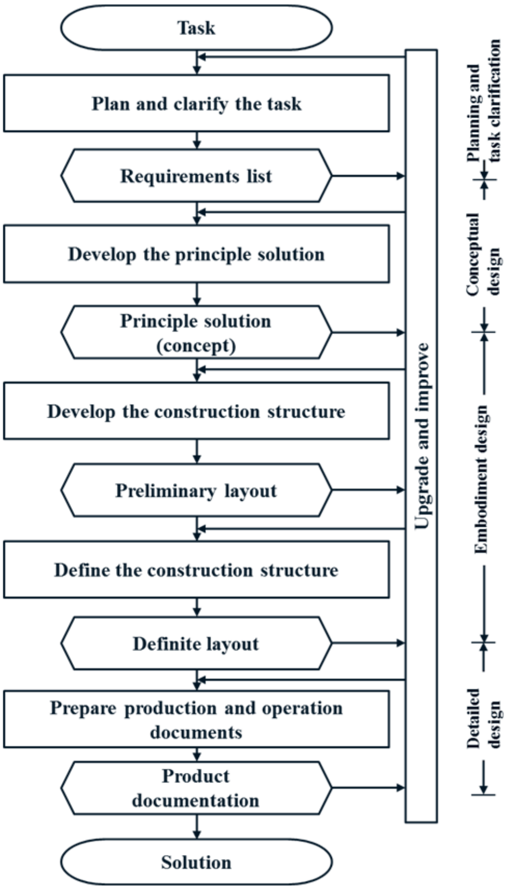


Figure 9: Product development Process by Pahl and Beitz (25)

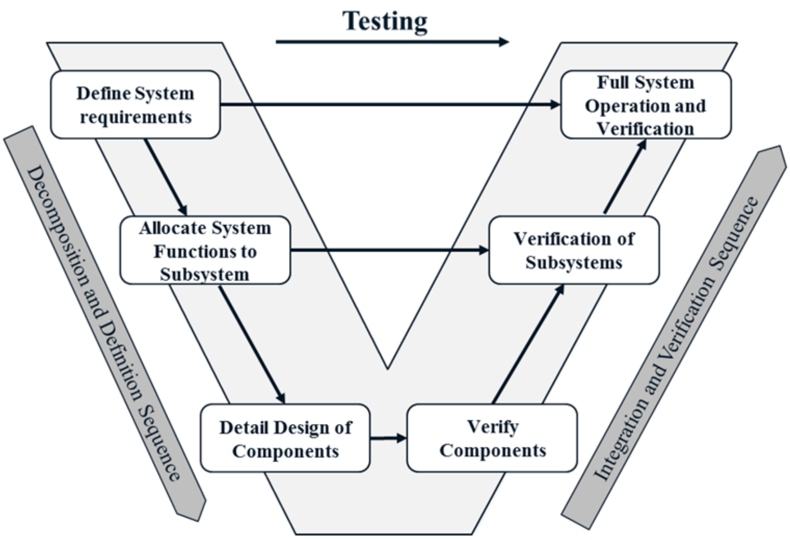


Figure 10: V-model redrawn from Blanchard and Fabrycky (58)

3.2.Robust Design theory and definition

Robust Design is the central concept and foundation for this research project. In the following, the theories of Robust Design, on which the current work is based, are presented and discussed. Robust Design was first introduced by Japanese quality engineer Genichi Taguchi in the 1950s who was at the time employed at the electrical communications laboratory of Japan's telephone and telegraph company and challenged with low quality raw materials and manufacturing equipment after World War II (19). Rather than trying to eliminate variation he developed a methodology addressing the sensitivity to variation of the products. As Robust Design became a major success factor in Japan's quality engineering, he popularized the ideas to the US at AT&T Bell laboratories in the 1980s followed by uptakes in major companies like Ford Motors and Xerox Corporation (18,19,39). His motivation for robust design arises from his notion of quality to be twofold:

1. "Product quality: what consumers desire (e.g., functions or appearance)
2. Engineering quality: what consumers do not want (e.g., functional variability, running cost, pollution)" (10)

In Taguchi's eyes the best solution to a problem is the one meeting the customer requirements with the lowest cost to society (39). Variability and inconsistent functional performance is therein seen as major cost for society.

3.2.1. Quality loss function

The essential difference between Robust Design and conventional quality initiatives is its quality maxim, which says that not all items that lie within specification limits are equally good (39). This paradigm can be explained with the quality loss function which describes how a deviation of the functional performance from a target value impacts the perception of quality, i.e. loss to the society.

In traditional quality assurance and control, a quality characteristic is checked against some defined specification limits and judged to be either acceptable/pass (being inside the limits) or not acceptable/reject (outside the limits). The notion of quality loss can therefore be described with a step function as shown in Figure 11a. In contrast, Taguchi associates a loss of quality with any deviation from the target (Figure 11b). The implications are evident. For a company that follows the step-wise quality loss paradigm, two products that have almost the same performance, one just inside and one just outside the specification limit, have the two opposite quality outcomes pass and reject. This veils potential quality problems and lowers the willingness to pursue quality improvement. It further bears the risk of sudden drops in yield for minimal process drifts or other changes. Taguchi's quality loss paradigm fosters efforts to produce products performing on target which prevents the mentioned risks.

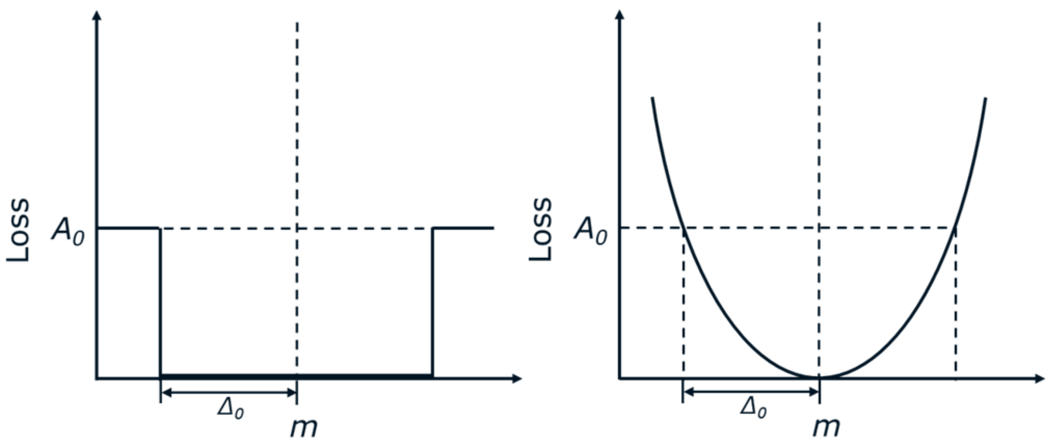


Figure 11: a) Step Quality Loss function; b) Quadratic Quality Loss function (18,19)

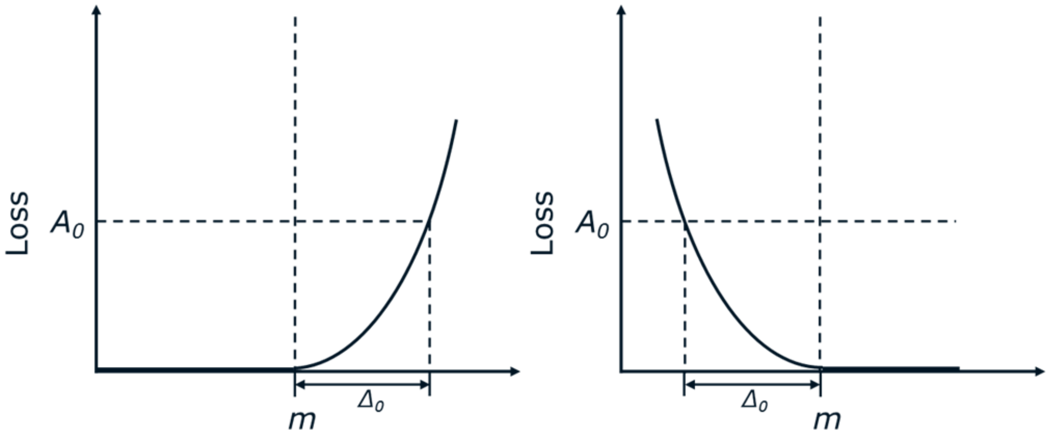


Figure 12: a) Quality loss function Smaller-the-better, b) Quality loss function Larger-the-better

Generally, Taguchi differentiates between three different types of requirements (18):

1. Nominal-the-best (Figure 11a, Figure 11b)
2. Smaller-the-better (Figure 12a)
3. Larger-the-better (Figure 12b)

m denotes the target value for a functional performance and A_0 the (monetary) loss to society at a variation Δ_0 from *m*, "where the product would fail half of the applications" (19). The quality loss function relates the functional variation to a loss to society and therefore engineering to economics (39). Table 3 summarizes the mathematical expressions for the quality loss *L* of a functional performance *y* for the three requirement types. The table also includes the average loss $\bar{L}$ for a population of *n* functional performances y_i which can be derived from the mean square deviation. σ^2 and μ denote the variance and mean of the functional performances respectively.

Table 3: Quality loss functions

	Nominal-the-best	Smaller-the-better	Larger-the-better
Loss	$L(y) = \frac{A_0}{\Delta_0^2}(y-m)^2$	$L(y) = \frac{A_0}{\Delta_0^2}(y)^2$	$L(y) = A_0\Delta_0^2\left(\frac{1}{y}\right)^2$
Average loss	$\bar{L} = \frac{A_0}{\Delta_0^2}[\sigma^2 + (\mu-m)^2]$	$\bar{L} = \frac{A_0}{\Delta_0^2}[\sigma^2 + \mu^2]$	$\bar{L} = A_0\Delta_0^2\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{y_i}\right)^2\right]$

3.2.2. Robustness definition

The quality loss function as presented in the preceding section illustrates the differences between the traditional and Taguchi's paradigm of quality engineering.

There are several definitions for "robustness" from various sciences including engineering, computer, natural and social sciences. The IEEE (59) defines robustness as "the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environmental conditions." Another definition of robustness by Holmgren (60) states that "Robustness signifies that the system will retain its system structure (function) intact (remains unchanged or nearly unchanged) when exposed to perturbations". Kitano (61) phrases the robustness as "property that allows a system to maintain its functions against internal and external perturbations". Gribble (62) adds that system robustness is "the ability of a system to continue to operate correctly across a wide range of operational conditions, and to fail gracefully outside of that range." Taguchi et al (18) define Robust Design as "designing a product that can function properly under various conditions of use." A more comprehensive definition is given by Fowlkes and Creveling (39):

"A product is said to be robust when it is insensitive to the effects of sources of variability, even though the sources themselves have not been eliminated."

Robust Design is therefore a methodology for designing products, devices, and production equipment to perform as intended, despite variation. In the literature, differentiation is made between three types of Robust Design:

- Type I: insensitive to variations in the noise factors as classically promoted by Taguchi (21)
- Type II: insensitive to variations in the product's design parameters (21)
- Type III: insensitive to variability and uncertainty in the system models (63)

The P-diagram (Figure 13) is commonly used to illustrate the different influencing factors of the behavior (response) of a product or process.

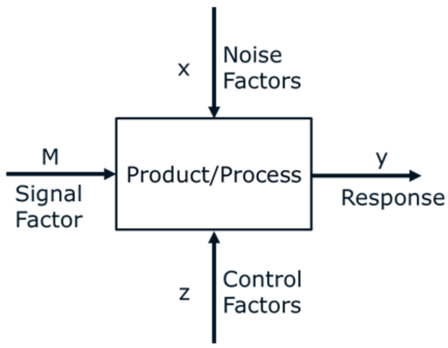


Figure 13: P-diagram (19)

A comprehensive discussion about the different notions of robustness was conducted in study 2 of this research (64) and will be presented in Chapter 4 of this thesis.

While the definitions mentioned above relate to the use phase which is most important to the customer, it needs to be stressed that variability is omnipresent in all stages of the product life and a major cost driver also in product development and production. The different sources of variation can be classified as shown in Table 4.

Table 4: Classification of sources of variation

Howard et al (32)	Fowlkes & Creveling (39), Phadke (19), Taguchi et al. (18)
Material	Unit-to-unit noise
Manufacturing	
Assembly	
Load (use)	Outer / External noise
Environment / ambient conditions	
Time-dependent (creep, wear, corrosion)	Inner / deterioration noise

Maintaining functional performance under variation in the input and environmental condition is common in the definitions stated above. This notion of robustness is closely related to the concept of reliability which is defined as “the ability of an item to perform a required function under stated conditions for a specified period of time.” (ISO 8402). The concept of reliability is based on the occurrence of failures and clearly limited to a predefined mission profile and time which entails variability which is a major driver for performance deterioration and finally for failure. Robustness can therefore be seen as a prerequisite and strategy to ensure reliability (19).

3.2.3. Transfer function model

The Transfer function is a mathematical description to relate the functional performance of a product to its influencing parameters usually in the form:

$$f = F(x_1, \dots, x_n)$$

Where *f* denotes the functional performance and x_i the *n* influencing parameters, which can be noise, signal or control factors (design parameters) (see Figure 13).

The graphical representation of the model can be used to illustrate, place and describe Robust Design efforts. The gradient of the graph represents the sensitivity of the functional performance to the respective design parameter (Figure 14). In the case of a non-linear transfer function, this gradient is dependent on the target value of the design parameter. With information about the variation (probability distribution) of the design parameter, for example from process capability databases (see for example (65)), the variation in the functional performance can be calculated. The slope of the transfer function determines the spread (width) of the functional performance probability distribution. From a production perspective a low sensitivity is appreciated allowing wider tolerances without compromising the variance of the functional performance, i.e. product quality. Influencing the propagation of variation is a central concept of Robust Design as discussed in the previous section.

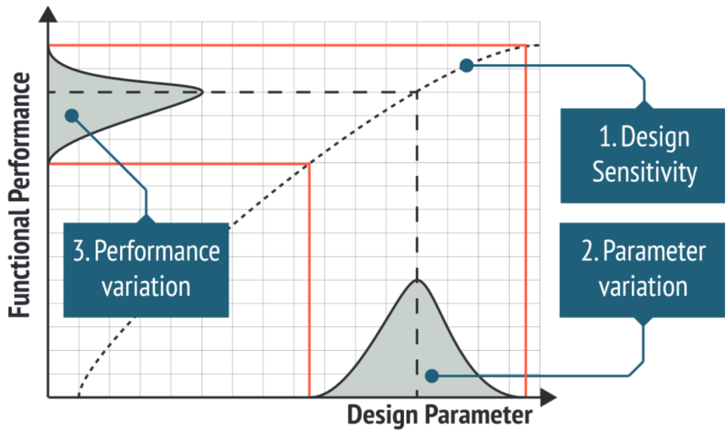


Figure 14: Transfer Function model redrawn from Ebro (28)

3.3. Frameworks related to Robust Design

3.3.1. The Taguchi method

The so-called Taguchi method was the first framework incorporating the ideas and mind-sets of Robust Design with quality loss occurring with any deviation from the target performance and is still used in developing companies. The goal is to achieve an optimal trade-off between functional performance and cost, where cost includes the cost to society due to variation from the target performance.

Another paradigm shift is promoted in the focus and sequence of designing for performance and quality. In contrast to the conventional approach in which a function is first designed to its performance target and then checked for its variance in practice, the sequence is turned around in the Taguchi method with the variance of a function being addressed first before adjusting to target. Taguchi argues that in that way a costly trial and error development can be avoided (18).

3.3.1.1. Signal – Noise-Ratio

A central metric for robustness in the Taguchi method is the Signal-to-Noise ratio (SN ratio). The SN ratio is a quality metric from the communication industry setting the power of the signal in relation to the power of the noise for example for receivers (66).

$$SN\ ratio = \frac{power\ of\ signal}{power\ of\ noise}$$

Taguchi adapted the SN ratio for the evaluation of functions and processes with respect to their influencing factors. In the Taguchi method it is distinguished between the dynamic and static SN ratio. The dynamic SN ratio describes the ratio of the power of proportionality between control and output to the power of variability for the entire range of a parameter. It therefore evaluates a dynamic quality characteristic over a range of values where the target is adjustable like for example the tone scale for printers (39). It aims to "optimize the function rather than just a single result" ((39) p. 119).

$$SN\ ratio_{dyn} = \frac{power\ of\ signal}{power\ of\ noise} = \frac{(sensitivity)^2}{(variability)^2} = \frac{\beta^2}{\sigma^2}$$

The static signal to noise ratio is used for fixed target problems (66) and describes the ratio between the power of mean to the power of variability around the mean (39). As previously described, there are three classes of requirements – smaller-the-better (STB), larger-the-better (LTB) and nominal-the-best (NTB). Depending on the type of requirement, the SN-ratio can be derived with the respective mean square deviation (MSD). y_i are the observed *n* functional responses, σ^2 and μ the population variance and mean respectively.

1. Smaller-the-better

$$SN_{STB} = -10\log(MSD) = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(y_i)^2\right] = -10\log(\sigma^2 + \mu^2)$$

2. Larger-the-better

$$SN_{LTB} = -10\log(MSD) = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}(1/y_i^2)\right]$$

3. Nominal-the-best

$$SN_{NTB} = -10\log(MSD) = -10\log\left(\frac{\sigma^2}{\mu^2}\right) = 10\log\left(\frac{\mu^2}{\sigma^2}\right)$$

The SN ratio is inversely proportional to the quality loss and makes a monetary evaluation possible (18,66). The logarithmic transformation magnifies the differences between parameters and changes the units to decibels. Another advantageous property is that multiplicative changes become additive, "thus making the metric proportional to relative quality" (39).

3.3.1.2. Phases

Taguchi distinguishes between 3 main phases of Robust Design: System design, Parameter design and Tolerance design (18,19,39).

1) System Design relates to the concept and embodiment of a design solution addressing the functional requirements of the product. Tools which are often associated with this phase are Quality Function Deployment (QFD), dynamic Signal-to-noise ratio optimization, theory of inventive problem solving, DoE, competitive technology assessment and Pugh concept selection.

2) In the Parameter Design phase the design is optimized for robustness. Designed experiments are used to gain understanding about the system behavior and the sensitivity of design parameters and noise factors, followed by the optimization of the static signal-to-noise (SN) ratio. The core idea is to utilize non-linearities and interactions between control and noise factors (11) with the aim to find the best control parameter setting that minimizes the functions' sensitivities to noise without negatively influencing the (manufacturing) costs (19). Couplings, i.e. interactions between control factors add complexity which "is harmful in Quality Engineering" since it complicates models and experiments and therefore increases the risks for inconsistent and non-reproducible results (66).

3) The third phase is the Tolerance Design which entails the optimization of the tolerances with respect to manufacturing costs and cost due to quality loss. This phase is therefore characterized by monetary trade-offs. Regularly used tools are quality loss functions, Design of Experiments and ANOVA (18,67).

All three phases can be applied in design, manufacturing process design and manufacturing. The Taguchi approach focuses mainly on type I Robust Design to optimize the robustness against noise factors utilizing systematic experimentation following orthogonal arrays in the Parameter Design phase. System Design and Tolerance Design play a less important role since Taguchi sees them as "specialist's territory" and "last countermeasure", respectively, to ensure a robust performance(18).

3.3.2. Axiomatic Design

Axiomatic Design is another influential theory in engineering design which connects design principles with Robust Design and system complexity considerations. Axiomatic design was originally proposed by Nam P. Suh. Following Suh, the design process comprises the mapping through four design domains: from the customer domain through the functional and physical domain to the process domain (Figure 15). The customer attributes (CA), functional requirements (FR), design parameters (DP) and process variables (PV) are characteristic vectors in their respective domain.

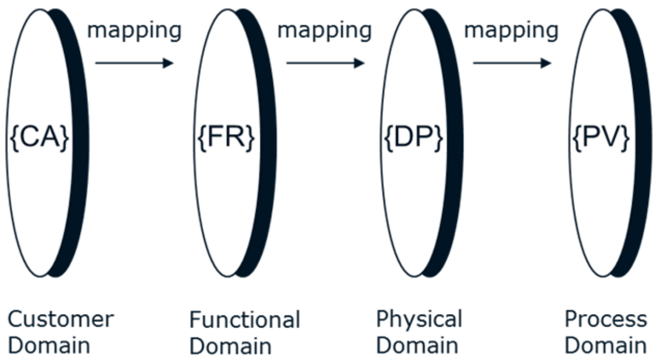


Figure 15: Design domains following Suh with characteristic vectors {x} (redrawn from (29))

Mathematically, the mapping is described with a linear system of equations in the form:

$$\bar{Y} = A\bar{X}$$

With the stiffness matrix *A* describing the sensitivity of *Y* to *X* (compare to slope in the transfer function model).

$$A_{ij} = \left[\frac{\partial Y_i}{\partial X_j}\right]$$

A product can be developed and described in a hierarchical manner going back and forth between the domains in a so-called zigzagging procedure to decompose the customer attributes to functional requirements further to design parameters and their associated process variables.

As the name "Axiomatic Design" indicates, this theory builds upon design axioms – some "self-evident truths or fundamental truths for which there are no counterexamples or exception" (29).

Axiom 1: *The Independence Axiom*. Maintain the independence of functional requirements (FRs).

Axiom 2: *The Information Axiom*. Minimize the information content of the design.

The first axiom promotes the independence of functional requirements, which aims at the coupling among functions. Coupling can lead to sub-optimal designs with trade-offs, that might require tighter tolerances and compromises. Three different types of coupling are distinguished:

1. Uncoupled designs: All functional requirements are independent with respect to the respective design parameters. The design matrix *A* is a diagonal matrix $\begin{bmatrix} x & 0 \\ 0 & x \end{bmatrix}$.
2. Decoupled designs: The design matrix *A* can be rearranged to a triangular matrix $\begin{bmatrix} x & 0 \\ x & x \end{bmatrix}$.
3. Coupled designs: The functional requirements are randomly coupled and the design matrix *A* is neither a diagonal nor can be rearranged to a triangular matrix $\begin{bmatrix} x & x \\ x & x \end{bmatrix}$.

Following the *Independence Axiom*, designs should be uncoupled or at least decoupled. This allows for individual adjustability of functions. Among the designs that fulfill Axiom 1, the design with the lowest *Information Content* shall be chosen. The Information Content I_i of a functional requirement FR_i is inversely proportional to the probability P_i that this functional requirement is fulfilled and derived as:

$$I_i = \log_2 \frac{1}{P_i} = -\log_2 P_i$$

The logarithmic transformation makes the information content additive for multiple functional requirements. The information content for a design/system with *m* FRs can then be calculated from the probability that all functions are fulfilled simultaneously.

$$I_{sys} = -\log_2 P_{\{m\}}$$

With

$$P_{\{m\}} = \prod_{i=1}^{m} P_i \qquad \text{For statistically independent FRs}$$

$$P_{\{m\}} = \prod_{i=1}^{m} P_{i|\{j\}} \qquad \text{For statistically dependent FRs}$$

This probability of success can be visualized as the area A_{CR} of the common range in a probability distribution diagram (Figure 16), i.e. by the overlap of the Design Range (success criterion) with actual System Range (output distribution).

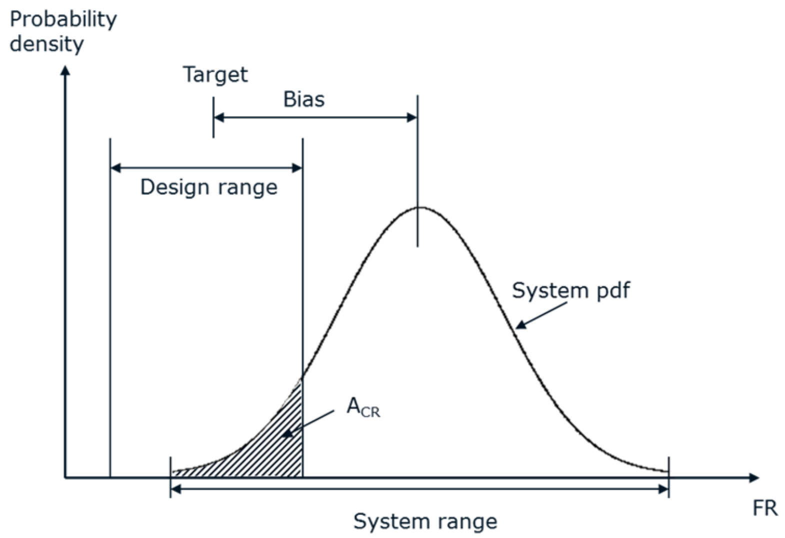


Figure 16: Common Range, redrawn from Suh (29) p. 41

A good design can accommodate large amounts of variation and still function as intended. This requires a robust design with low stiffness values in the design matrix *A* and a minimum bias. Both result in a low information content for the design. Similarities can be drawn to the Taguchi method as discussed in the previous section which aims to reduce variance and set to target in a two-step approach.

3.3.3. Variation Risk Management (VRM)

Variation risk management (VRM) was proposed by Anna Thornton as an approach to identify, address and manage risks due to variation in a holistic, process oriented and data-driven manner (31). The prioritization of quality efforts is in the core of the framework with "the ultimate goal […] to improve product quality, operational efficiency and productivity" (31). VRM is based upon quantitative and qualitative assessments of the influence of variability in production including robustness and process capabilities considerations, which makes it highly relevant for the research at hand. The framework consists of three main stages.

1. *Risk identification*

The aim of this phase is to gain a holistic and comprehensive view on variation starting from establishing what determines quality for the product. From there on, so-called Key Characteristics (KC) – "quantifiable features […] whose expectable variation from target has an unacceptable impact on the cost, performance or the safety of the product" – are identified and decomposed in a "variation flow-down" procedure consisting of five levels: Product KCs, System KCs, Assembly KCs, Part KCs and Process KCs. Figure 17 shows an exemplary and simplified KC flow-down for a car door.

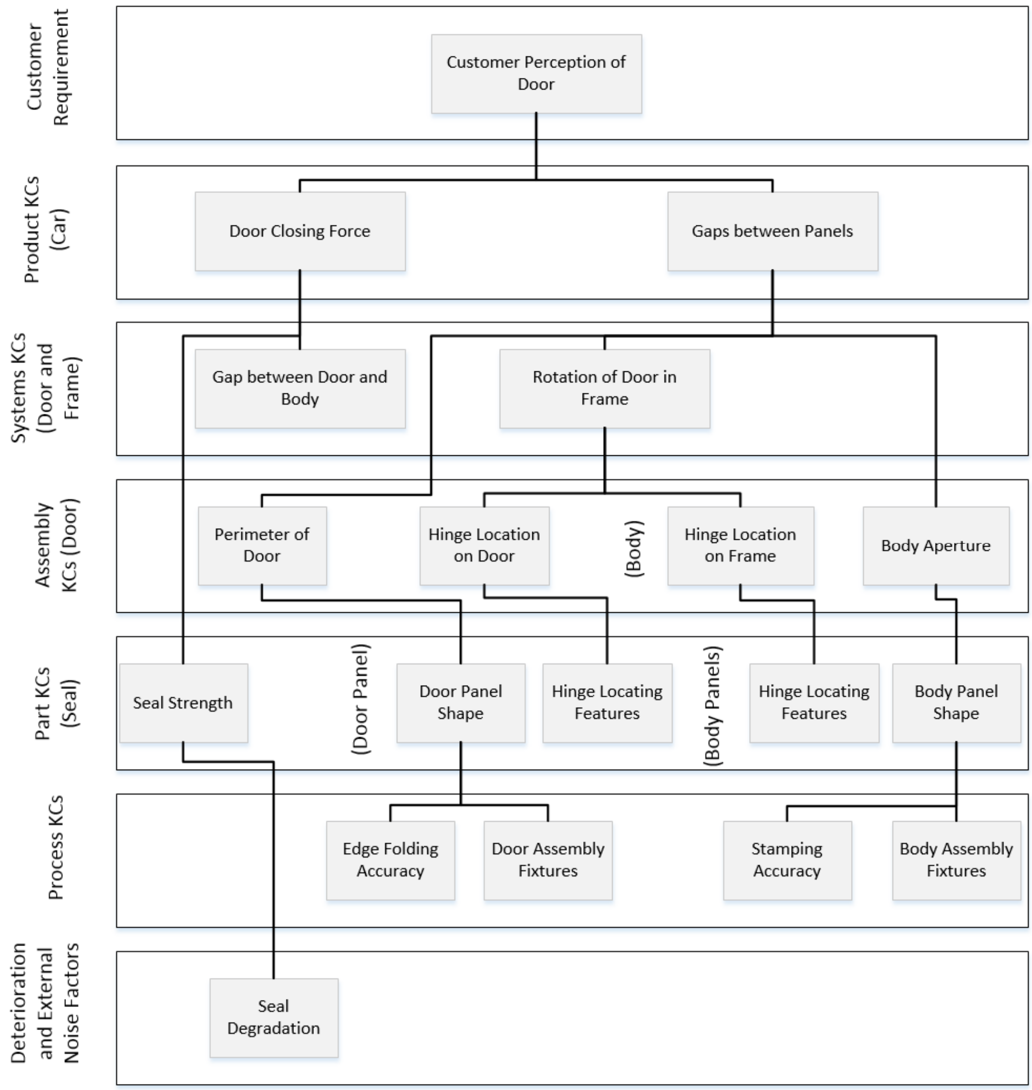


Figure 17: KC flow-down for a car door (redrawn from Thornton (31,68)**)**

2. Risk assessment

In this stage, the probability and cost of variation in the identified product KCs is assessed. For that the associated child KCs, i.e. part and process KCs are analyzed based on the predicted or measured defect rates and their cost in development and production, respectively. This assessment can be quantitative or qualitative (31). Pareto and contribution analysis are then used to prioritize efforts in the following mitigation phase. The data can be utilized to predict the final product quality by summing up the individual part variations or allocating allowable variations to single features in the form of tolerances.

3. Risk mitigation

The risk mitigation stage builds upon the information acquired in the risk assessment stage with the goal to reduce and optimize cost through design changes and process improvements. Generally, two strategies are followed: on the one hand the reduction of variation at the source and on the other hand the reduction of the design's sensitivity to variation. Common practices are cost/benefit trade-offs, Robust Design and manufacturing quality plans.

3.3.4. Variation Management Framework

The Variation Management Framework (VMF) was originally developed by Howard et al. (32) to explain and visualize Robust Design efforts. It consists of the four domains proposed by Suh in Axiomatic Design, namely the Customer, Functional, Physical and Process domain. The mapping between the domains describes the value, functional and structural composition of the product. The main visualization of the VMF is a coordinate system view similar to the one proposed by Whitney (41) with the domains on either ends of the axes. Utilizing Transfer Functions between the domains, variation in one domain can be mapped and propagated to the other domains. Figure 9 shows an example mapping for a pen lid removal force.

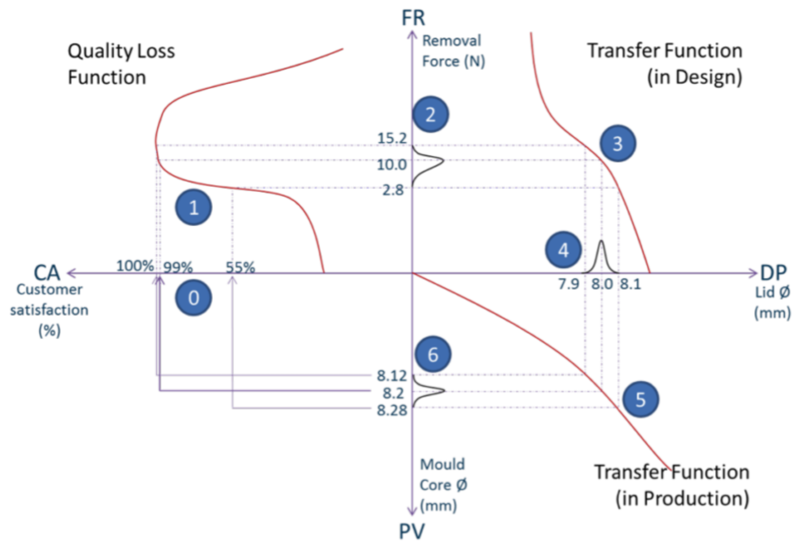


Figure 18: The VMF: modelling an example of a pen lid removal force from Howard et al. (32)

Seven different strategies exist to address variation in the different domains marked (0)-(6) in Figure 18. A successful and efficient variation management in product development and production is a monetary trade-off between the strategies. A short description of the variation intervention and trade-off points is given in Table 5.

Table 5: Variation intervention and trade-off points from Howard et al. (32)

0	Accept variation in the marketplace
1	Reduce sensory/perceptual robustness
2	Reduce outgoing variation by increasing outgoing quality control (product sampling)
3	Reduce the sensitivity of the design
4	Reduce ingoing variation by increasing ingoing quality control (part measurement)
5	Reduce production sensitivity
6	Reduce production variation

3.4.Structural complexity in engineering systems

In the field of product development, the notion of complexity plays an essential role. Especially with the emergence of large scale interdisciplinary engineering systems and ever more integrated products, the need for modeling and managing complexity has risen to increase the understanding and to prescribe a superior design (69). Besides the optimization of the system architecture utilizing modularization (clustering) and sequencing, the assessment of change and uncertainty propagation is of crucial importance. In that way complexity investigations become interesting from robustness point of view as dealt with in this research. Following the International Council on Systems Engineering (INCOSE) complexity is formally defined as

“the degree of difficulty in predicting the properties of a system if the properties of the system's parts are given” (70) p. 72.

This definition of complexity lays a common ground for the various definitions by scholars from this field of study. Summers and Shah (53) distinguish three different notions of complexity. Firstly, complexity related to the “information that is contained within a problem”, which is in line with the “Information Content” in Suh’s Axiomatic Design as discussed in section 3.3.2. Suh defines complexity “as a measure of uncertainty on achieving the specified Functional Requirements”. “A design is called complex when its probability of success is low” (29) p. 40. The second notion of complexity discussed by Summers and Shah is related to the coupling and interconnectivity of a problem. Following this notion, Magee and de Weck (71) describe a complex system as “a system with numerous components and interconnections, interactions or interdependence […]”. Further, Summers and Shah present the solvability of a problem as a measure for complexity. Different approaches exist to measure and quantify complexity including complexity theory, entropy and information theory (72). Various scholars acknowledge that complexity is a large contributing factor to the robustness of a system. INCOSE notes that for complex products “(un-measurably) small perturbations in inputs or environmental conditions may result in unpredictable changes in behavior.” (70) p. 72. Gribble writes that “small changes to a complex coupled system can result in large unexpected changes in behavior, possibly taking the system outside of its designers' expected operating regime" (62).

a)

b)

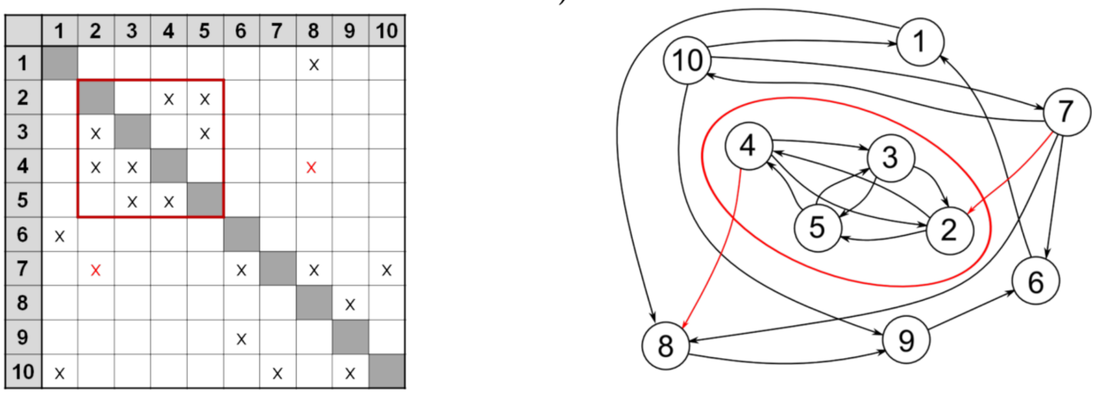


Figure 19: Structured system representation a) matrix-based and b) graph-based (redrawn from Eifler (73)**)**

Different methods exist to model, analyze and optimize system complexity as well as decompose a complex system. Most of them have their origins in graph theory, a branch in applied mathematics. Different properties of the system / network can be evaluated to predict its general behavior. For visualization purposes there is usually made a distinction between matrix-based and graph-based representations (74). Figure 19 shows the two representation of the same system: a) in matrix-form and b) as a graph. Graph visualizations have the advantage to visualize dependency chains and can be manually manipulated relatively easily (73). They are also used to visualize global patterns in a system/network. One of the most common matrix-based tools is the Design Structure Matrix (DSM), which was first introduced by Steward in 1981 (75). DSM is a network modeling tool showing a system's elements and their interactions and therefore structure in a square matrix where both axes are identically labeled and ordered (76). The interactions can be indicated either binary (as being present or absent) or numerically, where the strength, importance or impact of the interaction is captured (74). Different modifications and extensions exist including for example rectangular matrices mapping across different domains in so called Domain Mapping Matrices (DMM). DSMs and DMMs are often combined in Multiple-Domain Matrices (MDM) (7).

Other methods based on rectangular cross-domain mappings are the House of Quality (HoQ) in the Quality Function Deployment (QFD) methodology and Suh's design matrices in Axiomatic Design (29). The House of Quality is commonly used to identify and prioritize the Customer Attributes (what the customer wants) and map those against the Engineering Characteristics (how the Customer Attributes are addressed) (38). Figure 20 shows an example for the design of a car door.

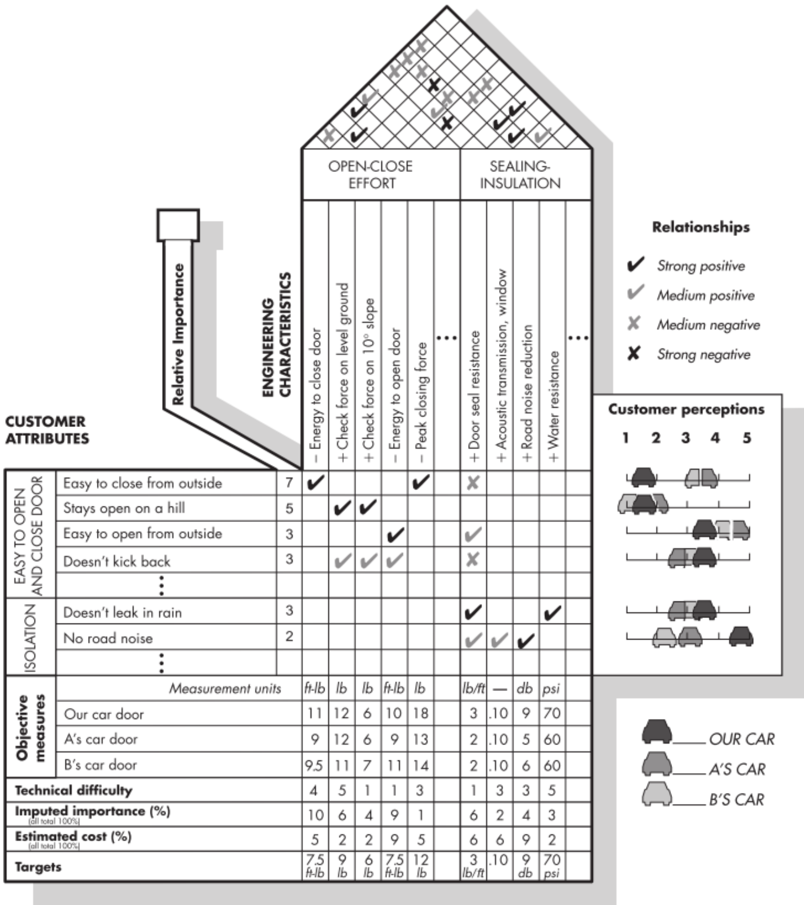


Figure 20: House of Quality (Example from Hauser and Clausing (38))

3.5.Numerical model building

The practical application of the Transfer Function Model as described in section 3.2.3 as well as many Robust Design techniques from classical Parameter Design in the Taguchi method to Robustness Optimization techniques require mathematical formulations and models of the functional behavior. Those numerical models are necessary to describe, evaluate and optimize the robustness of systems, products and processes.

The building and derivation of those models can be done in different ways. However, assumptions, limitations and accuracy of the model need to be understood. Generally, a distinction between two types of models can be made.

1. *Analytical models* are derived from natural laws or theories of physics or chemistry.
2. *Statistical models* are derived from data (observations). This data can be generated by running simulations (computational experiments) as for example Finite Element Analysis (FEA) or Computational Fluid Dynamics (CFD) or from physical experiments. The goal is to simplify complex system responses to surrogate models.

An efficient data gathering, i.e. experiment planning, and model deduction from the data is essential for the applicability of statistical models and will be described in the following.

Experiments (physical or computational) are means to generate knowledge about a functional response with one particular parameter setting. To identify correlations and to build a model, multiple data points need to be collected. The number of experimental runs depends on the complexity of the problem (i.e. how many influencing factors exist and how these are coupled) and the requirements on the model accuracy. Simple one-factor-at-a-time screening procedures can be used to investigate how the functional response changes due to one parameter. However, interaction effects between factors cannot be captured in this way. So called full factorial experimental designs, where every combination of parameter levels is tested, exhaustively capture the entire parameter space also yielding all interaction effects. However, full factorial experimental designs become very costly and time consuming with an increasing number of parameters and parameter levels due to the number of required experiments.

$$Number\ of\ experiments = m^n$$

- m: number of levels
- n: number of parameters

In most cases where functional responses are mainly driven by main effects rather than high-order interactions, this method is very inefficient. To address this inefficiency, fractional factorial experimental designs were developed. The idea is to design experiments that efficiently cover the parameter space while yielding information about the effects of factors and interactions to a certain order. As a result, certain interactions are deliberately confounded with other interactions or main effects, which means that not all factor interactions can be distinguished from the generated data. Data from designed experiments also bare other favorable properties with respect to subsequent modeling like mathematical independence of the factor effects due to the balance in the experimental design (39).

The first work on Experimental Design dates back to the 1920s conducted by Sir R. A. Fisher in the 1920s ("The Arrangement of Field Experiments" (1926) and “The Design of Experiments” (1935)) (77). Since then, Design of Experiments has been subject to deliberate research. Besides the classical statistical approach by Fisher, orthogonal arrays promoted by Taguchi, the variables search approach by Dorian Shainin (78) and the work by Box et al. (79,80) have influenced the research in this field (77).

Based on the generated data, different techniques can be used to build a surrogate model. The size, i.e. the amount of observations, and the limitations introduced by the experimental plan in the case of fractional factorial designs needs to be taken into consideration for modeling efforts. A common technique to generate a surrogate model is the response surface methodology (RSM) by Box and Wilson (81) which utilizes regression analysis fitting the data to a polynomial model. More recent are machine-learning techniques in the form of for example decision trees and artificial neural networks.

4. Results and Discussion

This PhD project comprises six single studies which jointly sought to answer the research questions and prove or disprove the hypotheses laid out in the introduction. All of them have been described in detail and published in scientific journals or peer-reviewed conference proceedings. The purpose of this chapter is to summarize and discuss the key results of the studies. This includes the discussion on whether the research questions have been answered and whether the research hypotheses can be accepted or rejected. This is followed by a validation and verification of the research project as a whole and a reflection on the limitations.

This research set out to investigate the quantification of robustness in complex products and the influence of complexity on robustness. This investigation is twofold including on the one hand metrics and indicators for the quantification and on the other hand the methods and approaches on how to quantify robustness. Different objectives, research questions and hypotheses have been formulated for this PhD project (see introduction chapter) to structure and guide the research.

4.1.Study 1 – Paper A

The first aim of this research project was to investigate and clarify the quantification of robustness. Study 1 comprised an investigation and analysis of the suite of Robust Design methods and tools to address Research Question 1:

Research Question 1

a) *What Robust Design methods, frameworks and processes exist to analyze and synthesize robustness?*
b) *How can a coherent Robust Design process be prescribed?*

4.1.1. Publication

Title: Mechanisms and coherences of robust design methodology: a robust design process proposal

Journal: Total Quality Management & Business Excellence

Citation: Simon Moritz Göhler, Martin Ebro and Thomas J. Howard (2016). "Mechanisms and coherences of robust design methodology: a robust design process proposal", *Total Quality Management & Business Excellence*, DOI: 10.1080/14783363.2016.1180952

4.1.2. Summary of results

The paper presents a Robust Design Process based on the mechanisms and coherences of the methods and tools associated with Robust Design. It is argued that eight different mechanisms exist of how a Robust Design method influences, interacts or describes the design to foster robustness against variation. A further classification with respect to the actual activity of the design or development engineer revealed four governing activities:

1. Firstly, ***Conceptual Design*** which addresses the actual composition of the design. This entails the choice of working principles that robustly fulfill the functional requirements of the product. It furthermore

includes other design choices related to the level of functional integration and complexity implicitly affecting the robustness of the design solution.

2. Secondly, the ***Measuring and Modeling*** of the system response. While conceptual design must include certain knowledge about how a particular functionality can be realized, the detailed understanding of the functional performance and behavior is in the core of Robust Design and the objective of this activity.
3. ***Processing and Evaluating*** the system response is a third kind of activity that is undergone in the process of Robust Design.
4. Another activity comprises the ***Detailing and Optimization*** of the design for robustness and minimal cost.

Table 6: RDM mechanisms and engineering activities

No	Mechanisms of RDM	Tools/Methods	What the designer does (Design Activities)
I	Robust concept design	• Selection of the working principle and the conceptual design solution	**1. Conceptual Design** In this context, conceptual design is understood as defining a new solution to a design problem, as opposed to scaling (see below).
II	Reduction of couplings between functions	• Axiomatic Design Axiom 1 • Separation/Integration of functions	
III	Reduction of number of influencing factors	• Axiomatic Design Axiom 2 • Design Clarity • Kinematic Design • Locating Schemes • Tolerance Chains	
IV	Design with robustness margins	• Safety factors wrt. structural and process capability data	
V	Measuring of system response	• Design of Experiments (DOE)	2. Data collection **(measuring) and modelling** of the system response
VI	Modelling of system response	• Analytical Transfer Function Modelling • Design Matrix • Response Surface Methodology and other data fitting methods • Variation Mode and Effects Analysis	
VII	Processing and evaluation of system response	• Design Structure Matrix (DSM) • Error Transmission Formula • Ishikawa / Fishbone Diagram • Monte-Carlo-Analysis (MCA) • P-Diagram • Pareto Analysis • Sensitivities Analysis	**3. Process and Evaluate** (Graphs, metrics, visualizations and deciding on further actions)
VIII	Scaling (optimization) of design parameters	• Optimization of transfer function or S/N-Ratio • Tolerance Management	**4. Detailed design and scaling (optimization)** of parameters and tolerances

Table 6 summarizes the results of the analysis of the Robust Design toolbox with its 23 methods and tools. It lists their underlying mechanisms and relations to the engineers' activities.

From the design activities, it was concluded that there is an underlying inherent sequence in which the activities and therefore the methods are linked together. "The coherences of the methods and activities form the process", i.e. the four activities can be arranged in a logical order of application forming an iterative reoccurring process that is undergone in every stage of the development process (see Figure 21).

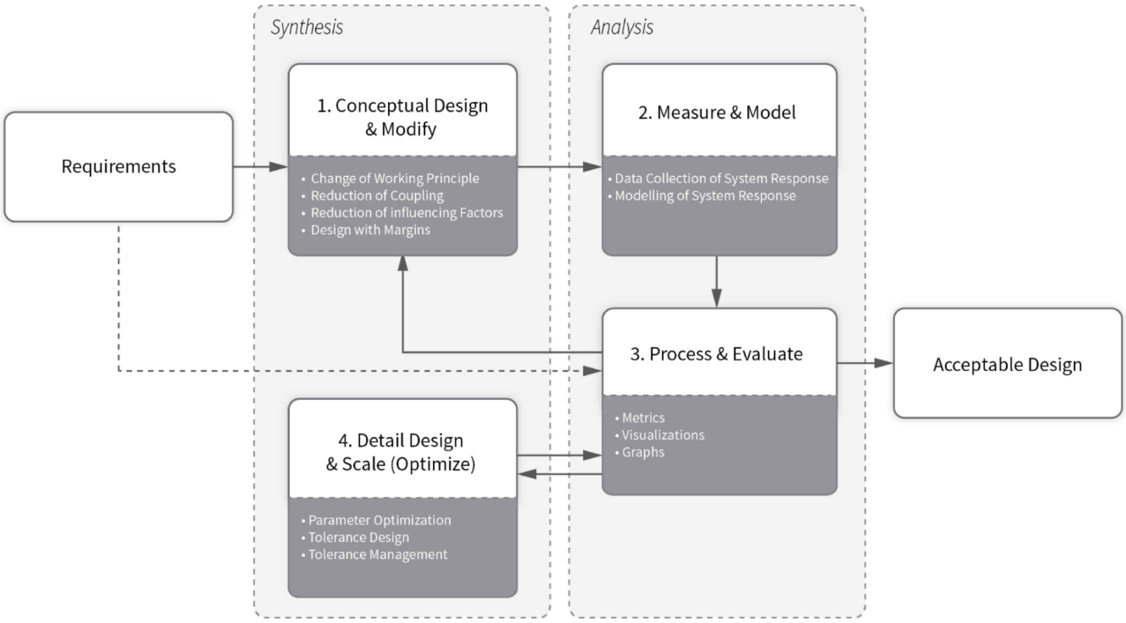


Figure 21: Proposal of a Robust Design process

4.1.3. Discussion and reflection

The research question is formulated open and includes a familiarization with the overall topic of Robust Design acting as support for the Research Clarification stage (40). The analysis revealed that there is currently no coherent Robust Design process available. Robust Design is rather seen as part of a larger strategy like in Design for Six Sigma or Variation Risk Management. Various methods were identified which are associated with Robust Design but are perceived as single standing patchwork of efforts for the improvement of robustness. The proposed process, with synthesis and analysis activities being conducted in an alternating manner, has some similarities to Property-driven design (PDD) by Weber (82) that features so-called "Synthesis-Analysis-Evaluation Cycles" that are conceptually similar to the activities 1-3. Optimization (part of activity 4) is not explicitly discussed in PDD. The framework of Characteristics-Properties Modelling (CPM) / PDD was developed as an overarching theory to integrate many existing approaches to product development. It is interesting to note that the research at hand, even though taking the departure from a different view point, namely analyzing Robust Design methods and tools, arrived at a similar process description.

The study also shows that the evaluation and quantification of a design's robustness plays an essential role in checking and improving a design to achieve a variation insensitive design. "You cannot improve what you cannot measure" (39). The results of the study answer research question 1 and lay the basis for the remaining PhD studies in the form of an understanding of the state of the art Robust Design and the different mechanisms that are utilized to influence, explore and describe robustness.

4.1.4. Study evaluation

To evaluate study 1, the methodology of logical verification and deductive reasoning as well as validation by acceptance (52) is applied. Logical verification is shown with:

Consistency: The model of the Transfer Function was used to analyze the methods in an objective and consistent manner. The succeeding categorization and derivation of a Robust Design process was conducted through logic and deductive reasoning to ensure consistency.

Completeness: For this study, four different sources were utilized to gather methods and frameworks related to Robust Design. A clear definition and delimitation of a "Robust Design tool" ensured a rigorous and complete selection of the methods. With respect to the categorization, it could be shown that the defined categories are mutually exclusive and collectively exhaustive meaning that all methods could be categorized without ambiguity into one and only one category.

To validate the usefulness, different application cases are discussed in the article. This includes the use of the categorization and Robust Design process to increase the engineers' understanding and awareness of their current Robust Design efforts. This is especially important for the successful implementation and integration in developing companies, since it was found that a tool-pull from the practitioners has a higher chance for an uptake than a tool-push from management (83). Another possible application was presented with respect to the building and establishing of a company Robust Design toolbox.

4.2. Study 2 – Paper B

Motivated by the ambiguity of the term "robustness" and the various ways that robustness is quantified in the literature and in practice, in this study, a systematic literature review was conducted to investigate into analyses and quantification of robustness to address Research Question 2:

Research Question 2
What robustness indices and metrics and ways to derive these exist and what are their differences and limitations?

4.2.1. Publication

Title: Robustness Metrics: Consolidating the Multiple Approaches to Quantify Robustness

Journal: Journal of Mechanical Design

Citation: Simon Moritz Göhler, Tobias Eifler, and Thomas J. Howard. "Robustness metrics: Consolidating the multiple approaches to quantify robustness." Journal of Mechanical Design 138.11 (2016): 111407.

4.2.2. Summary of results

From the systematic literature review, 38 unique robustness metrics were identified and analyzed based on the model of the Transfer Function with its three main entities, namely (1) the relationship between independent and dependent variables, (2) the functional limits and (3) the variation in the independent variables as shown in Figure 22.

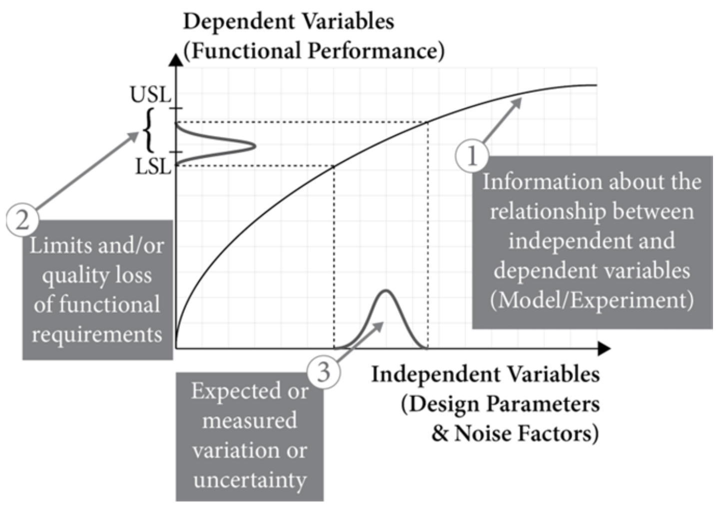


Figure 22: Robust Design framework to represent the propagation of variation

In addition to the information entities necessary to derive the individual metrics, the level of complexity that the metrics reflect, i.e. the number of functions and independent variables, has been investigated. The results are summarized in Table 7. The analyses revealed four different types of robustness metrics which each promote a different notion of robustness:

1) *Sensitivity robustness metrics* that quantify the influence of one or more design parameters or noise factors (independent factors) to the functional output
   → **robustness of a concept**

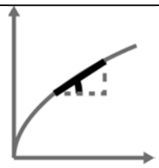
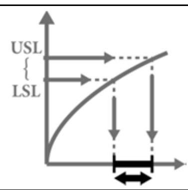
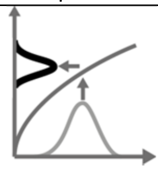
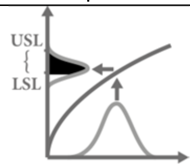
2) Metrics that describe the *size of the feasible design space* as measure for the robustness
   → **robustness of a design**

3) Metrics that evaluate different *expectancy and dispersion measures* of the functional output
→ **robustness of a function**

4) Metrics that evaluate the *probability of functional compliance* meaning that all functions are satisfactorily fulfilled under the influence of ingoing variation
→ **robustness of a product**

This means that besides the general classical concept of “robustness” as the insensitivity to the influence of variation, there are several other concepts and meanings of “robustness” that are used especially when attempting to quantify robustness.

Table 7: Classification scheme for robustness metrics

Robustness Metric Class		Sensitivity	Size of feasible design space	Functional expectancy and dispersion	Probability of functional compliance
Meaning in the TFM					
Necessary information entities	Model / Experiment	✓	✓	✓	✓
	Functional limits	-	✓	-	✓
	Expected / measured variation	-	-	✓	✓
Level of complexity (# of functions / # of independent variables)	1 / 1	✓	✓	✓	✓
	1 / n	(✓)	✓	✓	✓
	n / n	-	✓	✓	✓

4.2.3. Discussion and reflection

In the preceding study, it was established that measuring and quantifying robustness plays an essential role in Robust Design to prioritize efforts, make metric-driven design decisions, judge risks, predict yield and as cost functions in robustness optimization. The second study continued the research further investigating the different ways of robustness quantification and their associated interpretation for robustness.

From this study, it can be concluded that although the insensitivity to variation is in the core of the “robustness” definition, there is a further practical differentiation depending on the application and the information available, i.e. when in the development process the robustness is evaluated. The sheer sensitivity of a dependent variable on one or more independent variables is an important measure to evaluate the robustness of a concept or a design solution addressing a certain function. However, the practical implication with respect to the expected variation in the independent variables and the actual functional limits are neglected. Also, the interplay with other functions of the product and how these are coupled are not reflected.

The conceptual robustness (sensitivity) and design robustness (size of feasible design space) are independent of the (expected) variation. As companies are mostly interested in high yield rates and total functional variance, these metrics might not matter too much if process capabilities are sufficiently strong and ingoing variation can be controlled. In that case, functional (functional expectancy and dispersion) and product robustness (probability of functional compliance) metrics are more useful. However, products with low functional sensitivities to variation are more robust against unexpected variation and erroneous definitions of specification limits. This categorization of robustness metrics has practical implications on when to use what metric and what this means. The authors believe that this removes the ambiguity around term "robustness" supporting the use and communication of it in practice as for example in the formal introduction of robustness requirements to specification documents and design targets.

With the comprehensive list and categorization of robustness metrics from this study, Research Question 2 is considered answered.

4.2.4. Study evaluation

By applying a systematic literature review, a rigorous and comprehensive study was ensured. A deductive reasoning approach was used to explain the differences between the metrics and to explain their meaning and application based on the Transfer Function model. This also led to the categorization with the four different sorts of robustness metrics as presented. The fact that all metrics could unambiguously be placed in one and only one of the proposed categories indicates a viable categorization.

This study is furthermore deemed to be useful in academia and industry since it comprehensively clarifies the different facets of quantifying robustness which is especially important to conduct successful and efficient application of simulation-based and computer-aided design and design optimization. It also supports data-driven and objective decision making.

4.3.Study 3 – Paper C

From the author's experience in the aviation industry and from project work at Novo Nordisk device R&D - the main case company of this PhD project - a critical correlation between increasing complexity and robustness could be seen - especially in terms of contradicting requirements and successive necessary trade-offs. Designers and lead engineers reported in multiple instances the robustness challenges arising from coupling and functional integration. This led to the investigation of the influence of coupling, and further, the influence of contradictions on robustness with a case study at Novo Nordisk to address Research Question 3:

Research Question 3
What is the impact of complexity on robustness?

4.3.1. Publication

Title: The Contradiction Index - a new Metric combining System Complexity and Robustness for early Design Stages

Conference: ASME 2015 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Boston, MA

Citation: Simon Moritz Göhler, and Thomas J. Howard. "The Contradiction Index (CI): A New Metric Combining System Complexity and Robustness for Early Design Stages." *ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. American Society of Mechanical Engineers, 2015.

4.3.2. Summary of results

With the integration of ever more functionality in (mechanical) products, the risk of functional coupling and contradicting requirements rises making trade-offs necessary. This kind of complexity can lead to robustness issues which then again lead to tight tolerances. Small defects and variations can have knock-on effects throughout the product resulting in failure or non-compliance. The study revealed three different situations of coupling.

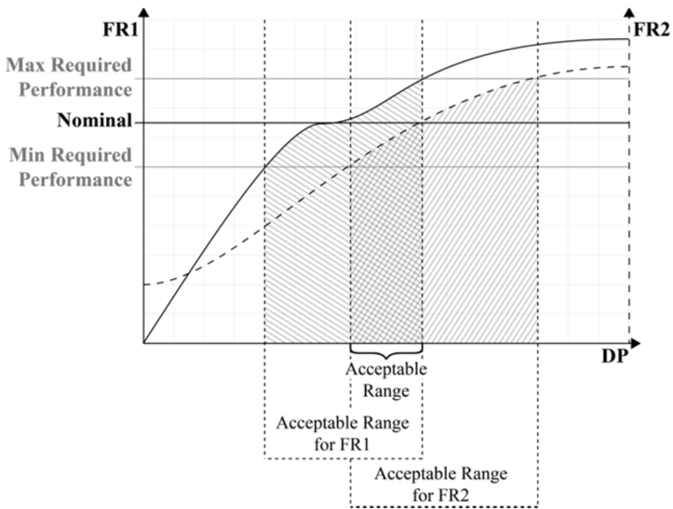


Figure 23: Coupled functional requirements of the kind "nominal-the-best"

Firstly, in the case of two nominal-the-best requirements, the acceptable range of the coupling parameter is potentially greatly restricted by each of the functions' upper and lower specification limits, making in most cases trade-offs necessary (Figure 23). Coupled functions with "nominal-the-best" requirements are therefore by nature contradicting.

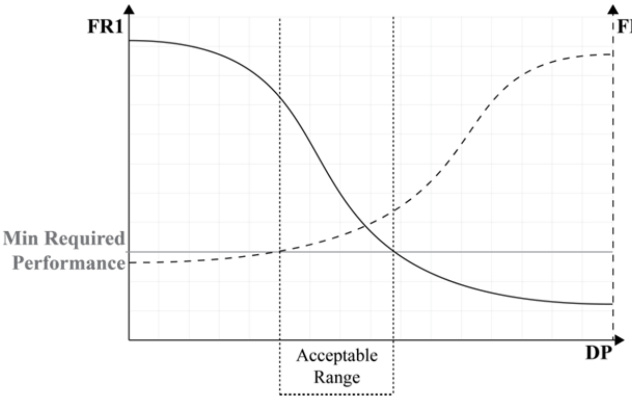


Figure 24: Negatively coupled functional requirements of the kind "larger-the-better"

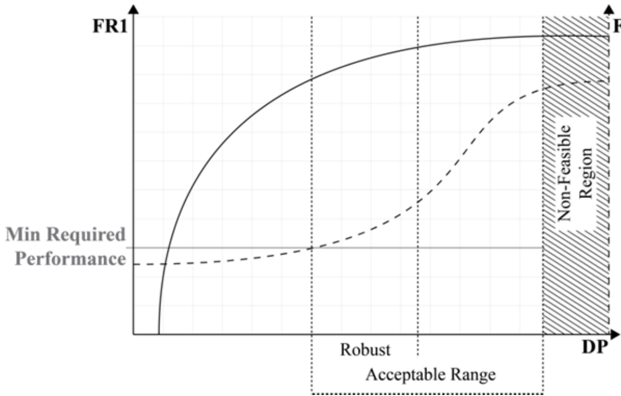


Figure 25: Positively coupled functional requirements of the kind "larger-the-better"

In the case of coupled functions with “larger-the-better” requirements (and analogously “smaller-the-better” requirements), it can be distinguished between two situations: firstly, a negative coupling as shown in Figure 24 which reduces the acceptable range and therefore robustness and secondly, a positive coupling with no detrimental effect on the acceptable range of the coupling parameter (Figure 25). With this notion of coupling and contradiction in mind, a methodology and metric - the Contradiction Index (CI) - was proposed to evaluate the level of contradiction of design solutions to foster robustness in early development stages with hardly any quantitative models at hand. This method consists of 4 steps:

1) Decompose the concept to organs (functional assemblies) and parts and allocate all FRs to the organs realizing the associated function.
2) Assign desired properties to every individual part that maximize its performance for a certain FR. These properties can be material related (e.g. electrical conductivity, hardness, strength, e-module etc.), geometry related (e.g. position, orientation, size etc.) or material and geometry related (e.g. stiffness, weight etc.). For the evaluation, the following 6-level scoring scheme was adapted from Pimmler and Eppinger (84) to evaluate the importance of the property (Table 8).

Table 8: 6-level scoring scheme adapted from Pimmler and Eppinger (84)

Required	+2	The property is necessary to fulfil the functional requirement.
Desired	+1	The property is beneficial for the performance of the function.
Unknown	+/-	For nominal is best requirements the influence of a property can be either desired or undesired
Indifferent	0	The property does not affect the performance of the function.
Undesired	-1	The property causes negative effects but does not prevent functionality.
Detrimental	-2	The property must be prevented to achieve functionality.

3) Estimate the number and nature of design parameters of a part towards a FR.
4) Evaluate the contradiction index on part and FR level.

$$Contradiction = \max(Importance| > 0) - \min(Importance| < 0)$$

$$CI_{Element} = \sum_{Properties} (Contradiction + No.\ of\ shared\ DPs)$$

A case study with the FlexTouch®, one of Novo Nordisk's insulin injection devices, was conducted to test the "Contradiction Index" and the hypotheses regarding conflicting couplings and robustness. As measures for design complexity and robustness, the number of design iterations and challenging tolerances for the individual parts was investigated, respectively. The analyses showed a positive correlation between the number of part design iterations and the CI (Figure 26) and a statistically significant correlation between the number of demanding tolerances and the CI (Figure 27).

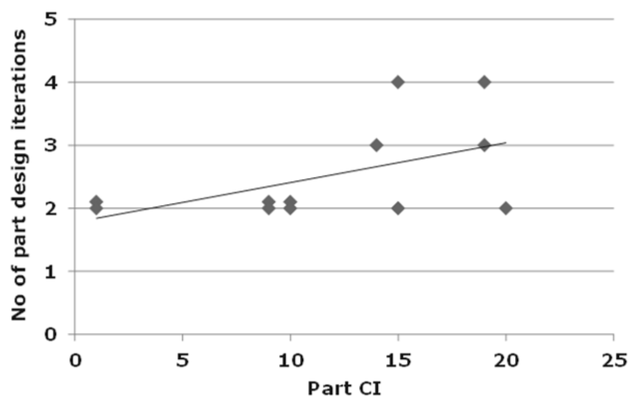


Figure 26: No. of Part Design Iterations vs Part CI

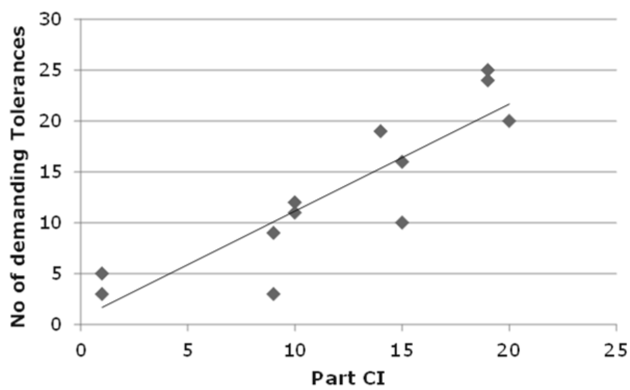


Figure 27: No. of demanding Tolerances vs Part CI

4.3.3. Discussion and reflection

In this study, the implications of functional coupling in general and negative coupling (contradiction) in particular are discussed on a theoretical basis and then investigated in a case study. The case study showed that the level of functional contradiction that can be measured already in early design stages has an effect on design difficulty and robustness of the final product. These are promising results. However, different aspects can be challenged and discussed: firstly, whether coupling in general and contradiction in particular are good measures for complexity. In the literature, different ways to quantify complexity are used. Those can be categorized in metrics that describe the information content, metrics that describe the coupling and interconnectivity and metrics that describe the solvability of the problem (53). The CI is a derivative and special case of coupling as a metric for complexity and therefore seen to be in line with the common understanding of complexity. The second aspect worth discussing is the use of number of part design iterations and challenging tolerances as measure for robustness in the case study. While the number of part design iterations can also be a measure of general design difficulty, the number of challenging tolerances is in the author's opinion a good indicator for robustness. Tolerances are set to control the ingoing variation to the final assembled product. The widths of the tolerance windows are a direct consequence of the robustness of the design and reflect the size of the feasible design space as discussed in study 2. The results of the case study show a clear correlation between the CI and the number of challenging tolerances. Tolerances are defined relatively late in the development process whereas contradictions in many cases can already be found in the conceptual design phase. This gives good potentials to use the CI as an early predictor and proxy to estimate robustness. The proposed methodology, furthermore, helps increasing the functional understanding of the design solution, which can be altered depending on the results and the judgment of whether critical functions should be uncoupled. However, the described case study is only a single data point finding these correlations and needs further studies to back-up the claims discussed.

4.3.4. Study evaluation

Following the validation square approach by Pedersen (51) as discussed in chapter 3, the study and its results can be evaluated by discussing the subsequent four points:

1. *Theoretical structural validity: is the general theory behind the support accepted and is the support consistent?*

   As discussed in the associated article and the preceding section, the consistency and acceptance of the theory as well as the CI have been ensured.

2. *Empirical structural validity: appropriateness of example case to show that support is useful.*

   The Novo Nordisk FlexTouch® insulin injection pen was chosen for the chase study consisting of "enough" functions and complexity (coupling) to conduct the analyses whilst not being over-complicated. Generally, the authors judge the example as appropriate.

3. *Empirical performance validity: measuring the usefulness of the results from applying the support.*

   The correlational model associating the CI with the number of challenging tolerances gives a clear indication of the performance and potential of the proposed metric. As discussed before, this study nevertheless needs follow-up studies to confirm the findings.

4. *Theoretical performance validity: evaluation of the generalizability of the usefulness of the support from the empirical case study.*

   Based on the comprehensive theoretical background and rational presented in the paper, the authors are confident in the generalizability of the method. This was further confirmed by the acceptance of the method by the designers and engineers at Novo Nordisk.

4.4. Study 4 – Paper D

Study 4 is a continuation and follow-up of the previous study to investigate the relation between complexity and robustness (Research Question 3). Study 3 was built upon a qualitative evaluation of contradiction and comprised only a single case study limiting the generalizability of the results. This follow-up study uses a model-based approach to investigate the association between complexity and robustness in a population of complex systems.

Research Question 3
What is the impact of complexity on robustness?

4.4.1. Publication

Title: A model-based approach to associate complexity and robustness in engineering systems

Journal: Research in Engineering Design

Citation: Simon Moritz Göhler, Daniel D. Frey, and Thomas J. Howard. "A model-based approach to associate complexity and robustness in engineering systems." *Research in Engineering Design* (2016): 1-12.

4.4.2. Summary of results

For this study, the hierarchical probability model (HPM) by Frey and Li (85) was adapted and extended to model complex systems. The model builds upon three characteristics and regularities of systems that have been observed in empirical studies of real-word systems.

1. Sparsity of effects:
   There are usually only a small number of factors or parameters in systems that are actually influencing the performance of the functions.
2. Hierarchy:
   Main effects are typically stronger than second-order interactions which are usually larger than third-order interactions and so on.
3. Inheritance:
   Interaction effects are more likely to be active if the interacting parameters' main effects are active.

The system model consists of *l* third-order polynomial equations representing the *l* functions of the system. The performance *y* is a function of the *n* influencing parameters x_i and their interactions up to third order.

$$y_l(x_1, x_2, \dots, x_n) = \beta_{0_l} + \sum_{i=1}^{n} \beta_{i_l} x_i + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \beta_{ij_l} x_i x_j + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \sum_{\substack{k=1 \\ k>i \\ k>j}}^{n} \beta_{ijk_l} x_i x_j x_k \quad l \in 1 \dots m$$

The coefficients β describe the strengths of the individual main effects and interactions on the function. They are derived following probabilities as seen in real-word systems concurring to the three characteristics mentioned above. To evaluate the robustness of a system, the system common range (yield, i.e. fulfilling all functional requirements simultaneously) was calculated from a Monte-Carlo simulation of 10^6 runs with uniformly distributed variation of 10% around the nominal of the influencing parameters.

250 systems were simulated with this model and the robustness evaluated. Furthermore, the number of couplings and the degree of contradiction were assessed to investigate associations between robustness and coupling as well as contradiction.

The analysis of the data shows no correlation between the normalized yield (robustness) and the number of couplings (Figure 28 shows a scatter plot). With p values of 0.13 and 0.11, the Pearson's and Spearman's tests suggest independence between the two. However, as can be seen from the scatter plot in Figure 29 there is strong correlation between the yield, i.e. robustness of the system, and the degree of contradiction. A linear least square fit with its 95% confidence bounds has been added to the plot.

$$f(c_{sys}) = p_1 \cdot c_{sys} + p_2$$
$$with$$
$$p_1 = -0.50$$
$$p_2 = 64.08$$

The association is statistically significant (p = 1.4e-36). This also confirmed by the Pearson's and Spearman's test.

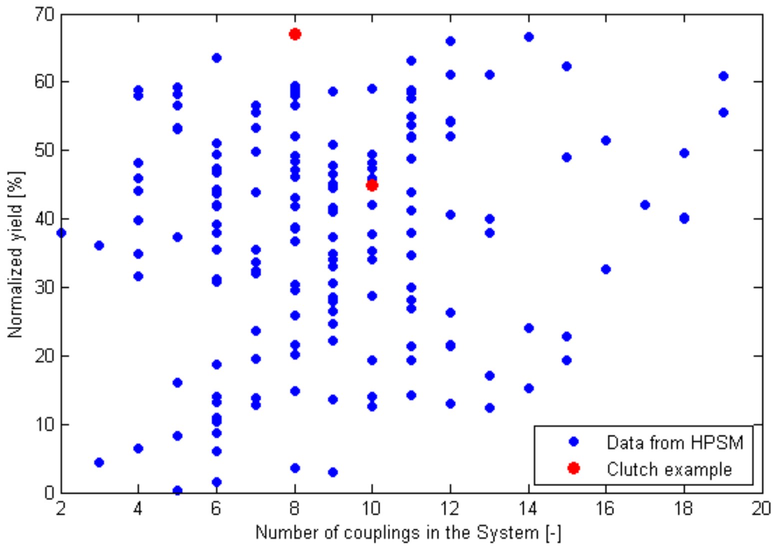


Figure 28: Scatter plot of normalized yield against no. of couplings

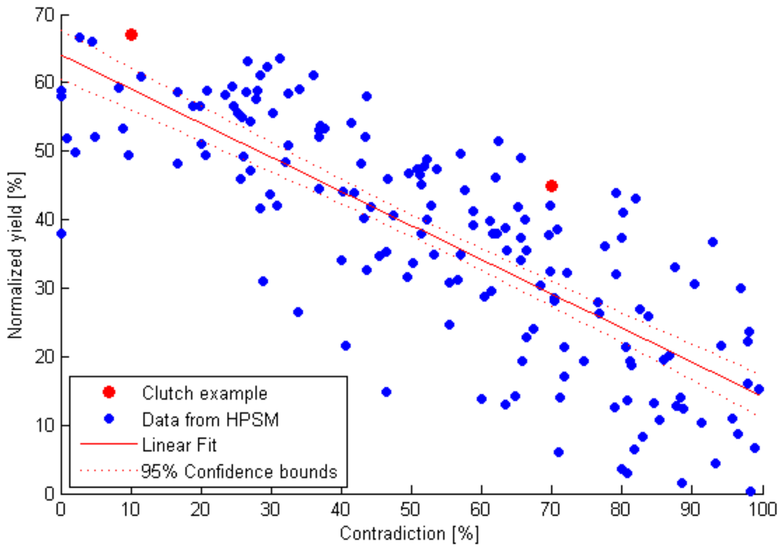


Figure 29: Association between normalized yield and contradiction

4.4.3. Discussion and reflection

To the authors' knowledge, the presented study is the first attempt to relate robustness and complexity quantitatively using a model-based probabilistic approach. As in the previous study, complexity was interpreted as the degree of coupling and interconnectivity following Summers and Shah (53). In contrast, Nam Suh, the author of the Axiomatic Design theory which is prevailing in this research area, defines complexity as "a measure of uncertainty […] in achieving a functional requirement" (86). This is synonymous with the information content defined in Axiom 2 which is derived from the probability that the design and system range overlap. This definition of complexity is in itself closely related to measures of reliability (i.e. the probability that a product fails) as well as the *probability of functional compliance robustness metrics* as discussed in Paper B. Suh limits complexity to the functional domain. However, even though Suh does not consider coupling as a measure for complexity, Axiom 1 – the independence axiom – addresses it. With respect to robustness, Suh showed that un- and de-coupled designs are inherently more robust than coupled designs for nominal-the-best requirements (29) p.124 ff. In this contribution, coupling was further specified with the notion of contradiction as defined in this study. It was found that for smaller/larger-the-better requirements it is actually not the degree of coupling but the degree of contradiction that is the main complexity related driver for non-robustness. This extends and differentiates the acknowledged view on coupling and robustness provided by Suh's Axiomatic Design (29). The knowledge about coupling and contradiction has some interesting and useful implications for the evaluation of the design solution especially in conceptual and early design. Assessments of the level of contradictions of design concepts give clues about the robustness of the final product. This insight can be used for concept selection, prioritization and focus of development efforts and resources as well as to assess the risk for non-robustness.

The results of this study confirm observations and results from the robustness and reliability analyses of complex products that report that even though some products are highly integrated (coupled) and therefore complex, they can be extraordinary robust and reliable (87). The maturity and evolution of those products are mentioned as the main driver for that. Linking these results to the results of the research at hand, a possible relation is that mature technical systems have undergone many design iterations where contradictions have been designed out and positive couplings have been more and more utilized.

In summary, this study has shown that complexity has a large influence on the robustness to variation of a product. However, the perception of robustness is slightly different than in the classical case where robustness is related to the functional performance being insensitive to variation. Complexity adds the dimension of specification limits which reduces the size of the design space as another limiting factor to how much variation is allowed. Suh (29) showed that this is generally true for coupled functions with nominal-the-best requirements. In this contribution, we showed that for smaller-the-better and larger-the-better requirements the level of contradiction determines the robustness together with the individual sensitivities of the functions.

This study contributed with new insights to answer the research question regarding the influence of complexity on robustness.

4.4.4. Study evaluation

The systems model used for this study was derived from the hierarchical probability model by Frey & Li (85) which builds upon empirical data for real-world engineering systems. The characteristics of the model therefore reflect the ones of systems observed in reality. Prevalent theories regarding “sparsity of effects”, “hierarchy” and “inheritance” were followed. Due to the prescribed and stringent model structure, consistency is ensured.

4.5.Study 5 – Paper E

In practice, Robust Design but also variation management including tolerancing is often limited to individual, single functions and parts, respectively. Comprehensive and product spanning efforts are especially difficult in multi-disciplinary development projects of complex products. In this study, a sensible and comprehensible way to decompose a complex product from its functional requirements to the design parameters was investigated to address Research Question 4:

Research Question 4
How can functional requirements efficiently be decomposed to support robustness and tolerance management of complex products?

4.5.1. Publication

Title: The Translation between Functional Requirements and Design Parameters for Robust Design

Conference: 14th CIRP Conference on Computer Aided Tolerancing (CAT)

Citation: Simon Moritz Göhler, Stephan Husung, and Thomas J. Howard. "The Translation between Functional Requirements and Design Parameters for Robust Design." *Procedia CIRP* 43 (2016): 106-111.

4.5.2. Summary of results

In the study, the practical aim was to address the lack of transparency and traceability of tolerances in complex and multi-disciplinary products. For this, a sensible decomposition of functional requirements (FR) to design parameters (DP) was proposed. Especially in cases where the functional requirements are of high abstraction level, relating those to the single design parameters can be extremely complicated, cumbersome and tedious.

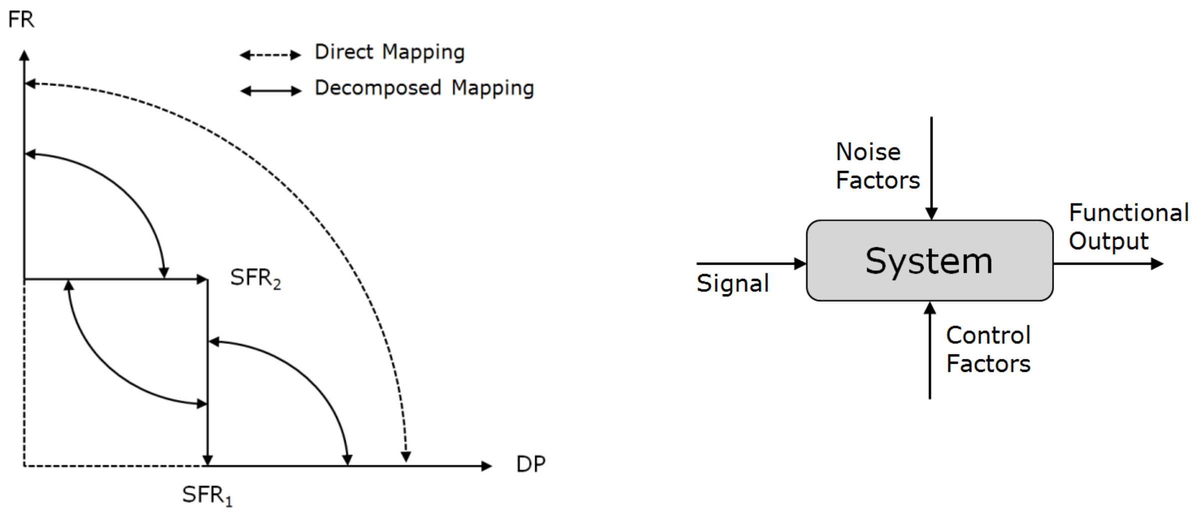


Figure 30: Mapping between FR and DP (left) and generic P-Diagram (right)

The top speed of a car, for example, depends on uncountable parameters. For efficient tolerancing and variation management, however, a thorough functional understanding and decomposition is necessary. A decomposition of functional requirements (FR) through sub-functional requirements (SFR) all the way to design parameters was proposed based on different sources of variation structured according to the P-Diagram (Figure 30). This yielded different levels of abstraction to describe a functional requirement top-down or bottom-up. Table 9 summarizes the 6 levels of sub-functional requirements. Level 1 to 3 relate solely to control factors including geometrical and material related properties. For level 4 and 5 sub-functional requirements, use and time are added as influencing parameters, respectively. Finally, level 6 consists of emerging functional requirements that combine level 1 to 5. The example case of a glue gun was used to demonstrate the strengths of the proposed decomposition. By posing requirements on the highest SFR level possible, no unnecessary constraints are introduced restricting the development process downstream. This enables an efficient tolerance analysis and allocation. Furthermore, it is possible to extent the current practice of geometry assurance of size, positions and orientations, to also include functional emerging properties.

Table 9: Description of Sub-Functional Requirement Levels

	SFR	Sources of Variation	Examples (mechanical)
Control Factors (Design Parameters)	Level 1	Single Dimensions and Material Properties (Basic definitions on drawing)	• Geometrical dimensions • Forms (GD&T) • Material properties (Density, yield stress/strain, Young's modulus, conductivity, resistance…) • Surface finish
	Level 2	Multiple Dimensions	• Volume, Area • Aspect ratio • Moment of inertia • 2nd Moment of area • Assemblies (relative dimensions, positions, orientations, flushness, gaps, overlaps)
	Level 3	Dimensions & Material Properties	• Weight • Stiffness • Rigidity
Use (Signal & Noise Factors)	Level 4	Dimensions & External Factors	• Stress
		Material Properties & External Factors	• Thermal Expansion (relative)
		Dimensions & Material Properties & External Factors	• Thermal Expansion (absolute) • Bending, buckling, distortion • Compression
Time	Level 5	Dimensions & Material Properties & External Factors & Time	• Creep • Corrosion • Wear
Functional output (behavior)	Level 6	Emerging responses and properties (combining Level 1 – 5)	• Friction • Efficiency • Power, Energy

4.5.3. Discussion and reflection

Common decomposition strategies of complex engineering systems use a structural decomposition, for example: system – sub-system – module – assembly – part – dimension. However, this view does not tell anything about the motivation and rationale as to why the structure is how it is. For the allocation and justification of tolerances and for efficient variation management as well as system evaluation this is essential. The proposed decomposition is based on a functional view on the system enabling a mapping of functional requirements on systems level to the individual dimensions and material properties of the parts. An example is presented in the associated conference article demonstrating the translation between functional requirements and design parameters. Further evaluation is however needed to finally conclude on the goodness of the proposed method.

In the wider sense, this decomposition can furthermore support the mapping of complex products to increase the functional understanding, also with respect to how changes or variation propagates through the product and which parameters might be coupled. It enables a holistic view on trade-offs, variation and robust design on systems level. This contribution therefore lays the basis for an efficient variation management and answers Research Question 4.

4.5.4. Study evaluation

The novel approach to map between functional requirements and design parameters proposed in this study is built upon deductive reasoning from a functional view on the engineering system. Consistency in the method and theory were ensured by structuring the decomposition by sources of variation following the commonly used P-diagram. In that way, internal conflicts in the theory were avoided. Furthermore, the authors are confident that any product and engineering system can be decomposed in that way. The proposed decomposition was applied to an example case. However, as mentioned before, further testing and development is needed.

4.6.Study 6 – Paper F

Informal conversations with industry partners and experience from project work hinted that although Robust Design and Systems Engineering are recognized and applied, variation related issues nevertheless are experienced especially in complex products. Silo thinking (i.e. insufficient collaboration and sharing of information between departments and disciplines), unquantified decision making and the uncertainty of the impact of change and variation in complex products are often named as causes leading to non-optimal designs and non-robust products. With the managerial push for "right first time" development and the associated enhanced virtual validation and verification, the holistic understanding of the product and how variation influences the functions has become even more important. All insights from the preceding studies of this PhD project have been combined to address Research Question 5:

Research Question 5
How can a holistic and coherent metric-driven Robust Design be supported throughout the development of complex products and systems?

4.6.1. Publication

Title: The Variation Management Framework (VMF) Tool for Robust Design

Journal: Journal of Engineering Design

Status: Submitted and in review

4.6.2. Summary of results

In this paper, a comprehensive study is presented investigating and addressing problems related to Robust Design and variation management for complex products. Firstly, a survey was conducted among Robust Design practitioners from industry at the Robust Design Day 2016 asking them to judge the severity of the issues postulated in the introduction of this section. It showed that between 55 and 70% of the delegates "agreed" or “strongly agreed” with the statements confirming the authors’ experiences. The question arose of how the aforementioned problems can be addressed and Robust Design of complex products be supported.

Based on the results from the preceding studies of this PhD research project the following 5 requirements towards a tool were formulated. The tool would need to…

1. …have a holistic approach to include marketing and production considerations to Robust Design to address issues related to silo-thinking.
2. …support a Key Characteristic approach to ensure applicability.
3. …support various fidelities of Transfer Function models including qualitative as well as linear and non-linear quantitative models to support type II Robust Design (63).
4. …exploit structural (complexity related) information to capture interaction related robustness issues arising from coupling (29) as well as trade-offs and contradictions (8,88) to support Robust Design from conceptual design onwards.
5. …enable and supply metrics like sensitivities (89), functional variance (64,89), size of design space (64), and yield rates (64) to monitor and prioritize efforts and make quantified, objective decision for metric-driven Robust Design.

Various tools and strategies to support Robust Design and variation management exist and were reviewed with respect to the 5 requirements listed above. However, even though they are very useful in various situations in the development process, none of them support Robust Design in a holistic and metric-driven way from the initial to the final design including structural and functional information. Based on the Variation Management Framework with its holistic approach to variation including marketing, design and production a tool was developed to comprehensively capture, process and present information and models of different fidelities to support metric-driven Robust Design. The VMF Tool is based upon an object-relational database linking market, functional, design and process parameters. This allows capitalizing on structural and functional information to evaluate the robustness of a design as described in studies 2, 3 and 4 of this research. Figure 31 shows the structure of the proposed VMF Tool. Different visualizations and presentations of the data in matrix or graph form are offered to enhance the functional understanding of the engineers.

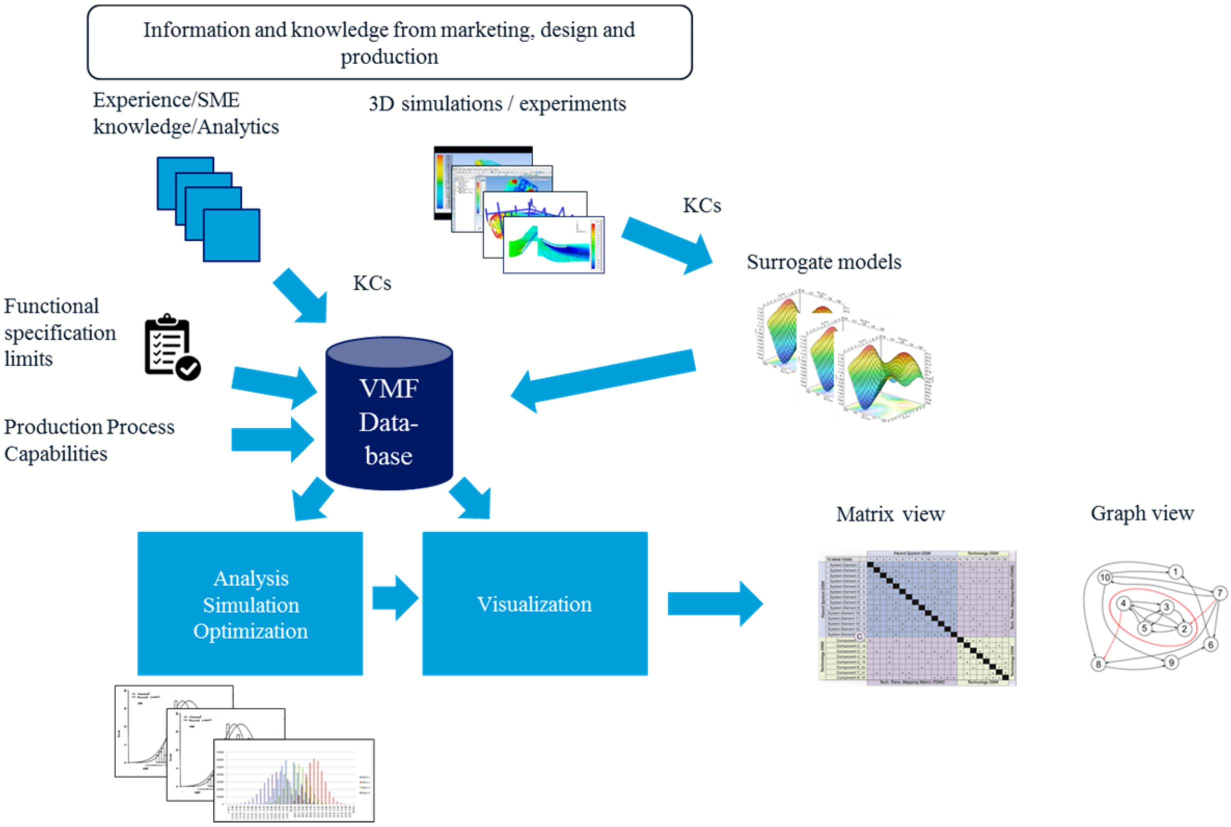


Figure 31: Holistic Variation Management Tool

Two case studies were conducted to test and evaluate the VMF Tool. The first one was run in a workshop format at the Robust Design Day 2016. It aimed to broadly evaluate the tool and its ability to address the issues around "silo-thinking", "unquantified decision making", "uncertainty of impact of change and variation" as well as "non-optimal designs and trade-offs" as outlined in the opening of this section. Five tasks were completed related to scenarios in detailed design and production and the participants asked in a survey to rate the suitability of the VMF Tool to solve above mentioned issues. 78% of the 40 responses that were returned "agreed" or "strongly agreed" that the VMF Tool could be a solution.

The second case study was an in-depth study of a sensor development for a medical device measuring a patient's levels of different parameters in the blood. From interviews and practice it became clear that due to the complexity of the product no one person had a comprehensive overview nor was there a central repository for the information leading to inefficient design iterations with potentially unwanted effects. More than 400 functional, design and process parameters were identified and mapped in the VMF Tool. In most cases, relationship and influences were known but not quantified. The strength of the VMF Tool is that it integrates the different fidelities of information. Figure 32 shows a matrix-view of the mapping of the sensor visualizing relations with "X", positive and negative influences with a "+" and a "-", respectively and the Nominal-range sensitivity (NRS) as relative measure for the propagation of variation (64).

An experiment with four engineers testing the usefulness and applicability of the VMF Tool showed an increased understanding of the product and a faster and more complete identification of influencing parameters to a function from a patchwork of analysis results compared to their current method of using spreadsheets. Positive feedback was also given to the ability of the tool to communicate between team members from different departments and backgrounds.

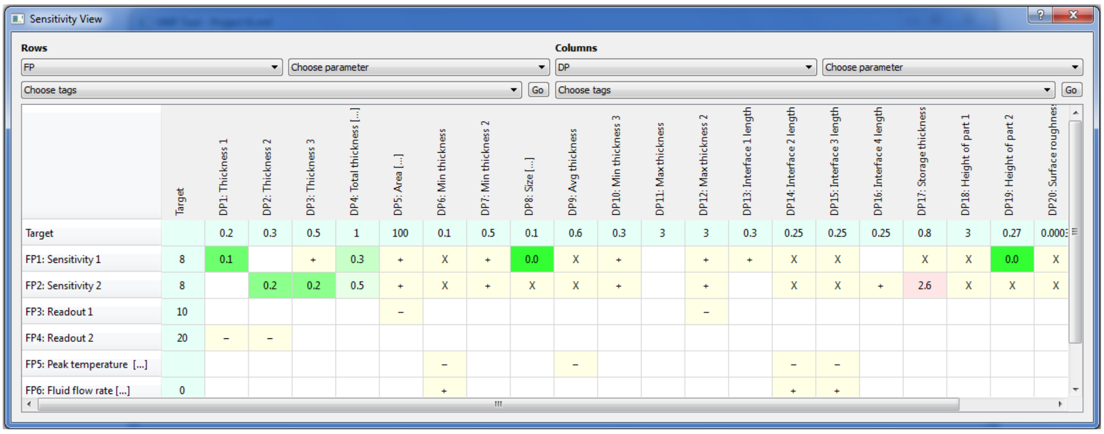


Figure 32: VMF Tool sensitivity view

4.6.3. Discussion and reflection

This study sought to investigate how holistic and coherent metric-driven Robust Design can be supported for complex products. The VMF Tool proposed in this contribution is an attempt to assist Robust Design by capturing, processing and presenting the data and information from a patchwork of analyses and expertise. The strength of the tool lies within the integration and conflation of all available information to all members of the development team. The holistic understanding of the product and the influence of variation propagating through the production, design and marketing domain is seen as key to "right first time" development of robust designs.

The tool enables the enhanced utilization of robustness metrics and indicators to increase the efficiency of variation management and Robust Design. It provides thereby also a quantifiable and objective basis for design decisions as well as for analysis and resource allocation. However, the filling and maintaining of the VMF Tool adds an additional step to the development process. The question arises when the extra effort pays off. A cost-benefit analysis as for other variation management initiatives is necessary. Generally, the level of complexity of the product and the criticality of robustness for manufacturing and for quality in the market have to be considered. It needs to be noted that the insight attained from the tool is dependent on and only as good as the information that is put in.

4.6.4. Study evaluation

The tool proposed in this study is based upon the body of knowledge of Robust Design and variation management. The theory is therefore established and consistent. Two case studies were run to test the applicability and usefulness of the tool in practice.

The first one was conducted in the form of a Robust Design workshop with specialist participants from industry who evaluated the VMF Tool positively in a survey following the workshop. Although the group of delegates was not representative, the results still indicate a good potential of the tool. The second case study showed the applicability and usefulness of the tool in the development of a complex product.

Even though only tested in these two case studies, the authors are confident that the usefulness of the tool would also be apparent in other applications. However, further testing and development of the tool itself and the software demonstrator including the improvement of the user interface are necessary.

4.7.Hypothesis testing

Two hypotheses were formulated in the opening of this PhD project, namely:

Hypotheses

A) The structural complexity of an engineering system has a significant influence on its conceptual robustness against variation.

B) A holistic and quantitative approach based on robustness AND complexity considerations can improve the functional understanding and support metric-driven Robust Design of complex engineering systems.

In the following, the hypotheses are tested utilizing the findings from this PhD research as presented and discussed in the preceding sections.

As the results from studies 3 and 4 showed, the structural complexity of an engineering system has an influence on its robustness to variation. It was shown that for smaller-the-better and larger-the-better requirements, a higher degree of contradiction related to a reduced robustness. Together with the results from Nam P. Suh who showed that for nominal-the-best requirements coupling in general results in a lower robustness, it can be concluded that hypothesis A can be accepted.

With respect to hypothesis B, studies 1 and 2 laid out the procedural and metric-related basis to develop the approach and tool proposed and tested in studies 5 and 6. The initial evaluation of the tool indicated a positive effect and good potential. Therefore, hypothesis B is considered to be tentatively accepted. However, further development and testing is required to fully accept it.

4.8.Evaluation of the research

In the following, it will first be laid out how the research fits in the existing body of knowledge thereafter further reflections will be given on how the research has been conducted as well as on its validity and usefulness.

4.8.1. Evaluation relative to the existing body of knowledge

In this PhD research project, the quantification of robustness and the associated support of Robust Design throughout the development and production stages have been investigated. A special focus was put on the influence of complexity, i.e. coupling and contradiction, to enable earlier predictions of robustness. Various researchers have worked on this topic more or less explicitly. Some of the greatest contributions were made by Nam P. Suh (29) who proposed two design axioms, namely the Independence and the Information Axiom, emphasizing the importance of designing functionally superior products and systems to not only reduce complexity but also increase robustness. He writes that (30) (real) complexity arises from many different reasons:

1. Coupling of FRs
2. Decrease in the allowable tolerance due to the presence of coupling terms
3. Lack of robustness (i.e., too large “stiffness” of the design matrix)
4. Wrong choice of DPs
5. Wrong decomposition of FRs and DPs

The results of the research at hand augment and extend these insights. Where Axiomatic Design is seen as a more abstract and higher level design paradigm, we combined and related it to quantitative methods as for example used in the Taguchi method (18), Robust Design Optimization (20) and generic sensitivity analyses (89). Also qualitative measures were considered benefitting from research done by Ebro (12). An application-driven research and approach to variation management was conducted by Thornton (31) and Dantan et al. (33), who utilized key characteristics identification and problem decomposition to reduce the intricacy of the problem and risk assessment, and mitigation to address it. The work at hand is seen as an extension to their frameworks in that way that the variation management is not only limited to the realm of geometry insurance and tolerances but supports metric-driven Robust Design.

In summary, the results of this research are in line with and extend the current body of knowledge. The core contributions of this research will be further discussed in the succeeding conclusion chapter.

4.8.2. Research verification and validation

The verification of this research is done by reflecting on the criteria completeness, coherence and consistency (52):

Completeness: As laid out in the preceding sections, all research questions guiding this research were answered and the hypotheses tested. Various methods were used to investigate the topic of quantifying robustness from different angles including the review of literature, archival analysis, case studies, system modeling and deductive reasoning to propose new solutions and approaches. Through this manifold investigation, we are confident that the field was thoroughly covered and researched, both in the academic and industrial sense.

Coherence: The studies contained in this PhD research project were carefully chosen and organized led by the research questions and hypotheses. Studies 1 and 2 investigated the procedural placement of robustness quantification in Robust Design and the different ways to quantify and define robustness, respectively. With that knowledge and the insights from studies 3 and 4 regarding the influence of complexity on robustness, the approach and tool as described and tested in studies 5 and 6 were developed.

Consistency: The methods and approaches proposed in this research are in themselves consistent and do not conflict with each other. Also, the knowledge and insights generated are consistent with current body of knowledge as discussed in the previous section.

The *validity* of the knowledge claims and results of this research were ensured by the rigorous use of a research methodology and triangulation using different sources and methods including the review of and comparison with the current body of knowledge. Furthermore, the usability, applicability and usefulness of the research results were discussed to validate the results as proposed by Blessing and Chakrabarti (40).

4.8.3. Limitations

The research presented in this thesis was conducted with a background and training in aerospace and mechanical engineering and at the Department of Mechanical Engineering at the Technical University of Denmark. With this in mind, the results and insights are limited to mechanical products and mechanical engineering systems. However, it is thought that many of the aspects coming from and discussed in this research are applicable also in other fields of engineering like electrical, chemical and software engineering.

From the content point of view, the process on how to generate and fill-in the data to the VMF as well as the procedural interactions with generic product development processes in practice were not entirely included in this research and need further investigation. Also, incomplete data and uncertainty as factors in robustness quantification and variation management require further research.

Another limitation is that the proposed methods and approaches have only undergone an initial evaluation with single case studies as discussed by Blessing and Chakrabarti for the *Descriptive Study II* (40). Further research and testing on the usability, applicability and usefulness are necessary to ensure generalizability. Also the implementation in industry requires assessment.

5. Conclusion

This chapter concludes this PhD thesis and includes a reflection on the research project as a whole. Starting with the presentation of the core contributions in an academic and industrial context the chapter continues with the impact and value of the research. Finally, suggestions for further research are presented and personal concluding remarks are given.

Designing products robust to variation is the key to reduce the cost of quality while still ensuring consistent and reliable products to the customers' satisfaction. The robustness evaluation and quantification from the early design stages onwards plays an essential role in this process enabling metric-driven design decisions and selections, prioritization of tasks and resources as well as monitoring and optimization of the design solution's robustness against variation. However, the analysis and evaluation of complex products and engineering systems is challenging especially early in the development. This does also apply to the quantification of robustness, which is a prerequisite for an efficient metric-driven Robust Design as well as for variation management.

In this PhD research project, the quantification of robustness has been studied from different angles. Among others, the different metrics and facets of robustness were researched and the influence of a design's complexity on the product's robustness investigated. It could be shown that the complexity of a design, manifested in the degree of coupling and contradiction, in fact has an impact on the robustness which allows robustness estimations already on conceptual level. Successively, the VMF tool was developed to comprehensively capture, present and analyze structural (complexity related) and functional information to support a holistic, metric-driven Robust Design and variation management throughout the development process and in production. The core contributions as well as the impact and value of this research are summarized in the following.

5.1.Core contributions

This research sought to shed light onto the quantification of robustness for complex products and engineering systems and contributes to the body of knowledge in various ways. The following core contributions have been made.

- Explanation of the mechanisms of Robust Design tools and methods – how do different tools influence and describe the design solutions they are applied to
- Prescription of a Robust Design process
- Summary and evaluation of metrics to quantify robustness
- Removal of the ambiguity around and clarification of the term robustness – nuances of and differences in the use of the term robustness
- Description of the relationship between robustness and complexity of a product
- The Contradiction Index as a method to qualitatively measure the level of contradiction of a design solution

- A method and framework to comprehensively decompose functional requirements to design parameters
- The augmentation and extension of the VMF to an operational tool to capture, communicate and analyze information to support metric-driven Robust Design for complex products

5.2. Value and impact of the research

In the following, the value and impact of this research are discussed from an academic and industrial perspective. What implications follow from the results and how can the results be applied?

5.2.1. Academic

The academic value of this research is seen in the clarification of the impact of complexity, and contradiction in particular, on the robustness of a complex product. Also, the description of the different facets of robustness as well as the mechanisms of Robust Design tools contribute to the understanding of Robust Design as well as robustness analyses and lay the basis for further research and development of methods and processes to support Robust Design and variation management.

5.2.2. Industrial

The industrial value and application of the results of this research are manifold. With the description of the mechanisms of Robust Design tools and methods and their categorization, it is possible to establish an organized and company specific Robust Design toolbox to ease the introduction and application of the methods and tools. This is furthermore supported by the proposed Robust Design process linking the tools to the individual activities of the engineers. Generally, the contributions made to the understanding of Robust Design and robustness metrics in particular have the potential to ease the communication and uptake of Robust Design in industry. With the removal of the ambiguity around the term robustness, the formal integration of robustness target to specification and requirements documents is conceivable.

Another value is seen in the Contradiction Index and the insights from the studies regarding complexity and robustness which enables the evaluation of design solutions in early development stages to support the concept selection. The case company Novo Nordisk continued assessing the contradiction of functions in further development projects after the case study was completed. It could also be seen that a paradigm shift occurred to include “function assurance” to the “geometry assurance” at Novo Nordisk.

The case companies also showed great interest in the VFM Tool and the capabilities of the software demonstrator. A strengthened communication about variation and robustness and a holistic approach to tackle related problems throughout the development and production of a product is seen as a promising extension to their product development processes.

5.3. Suggestions for further research

A PhD project is a time limited research and cannot follow all interesting and useful leads and ideas that are worth investigating to the end. While many aspects of robustness quantification for complex products and systems have been researched and touched upon in this project, different new research questions and ideas were generated. In the following, a few suggestions for further research in this field are presented.

5.3.1. Process and application of VMF tool

In this research, it was shown that the VMF tool offers great potentials to support the metric-driven Robust Design capitalizing on structural (complexity related) and functional information about the design solution. For the successful implementation, further research on the process on how to apply the VMF Tool as well as supporting case studies are required. Furthermore, the way to deal with incomplete data and uncertainty (aleatory and epistemic) plays an essential role for a full-fetched application of the tool in industry and needs investigation.

5.3.2. Further development of VMF software tool

In study 6, a software demonstrator for the VMF Tool was presented. Especially the scalability and automation potentials of a software solution make the tool interesting and applicable in an industrial context. However, further development of the software is necessary to include more features and improve the user interface. The integration to commonly used PLM systems with links to the individual analysis software can be of further benefit.

5.3.3. Variation management process

With increasing level of customization and complexity of products but also decentralized organization and global competition, an efficient variation management becomes necessary. The experiences from the research showed that the cooperation and communication regarding targets, specification limits and priorities across the departments of marketing, design, production and aftersales have great potentials for improvements. Often, competing KPIs (Key Performance Indicators) for the different departments hinder an efficient variation management. Research into the process on how to coordinate across the different departments to gather and utilize the available information in the most efficient way is seen as a great opportunity to support holistic and data-driven decision making. Initial ideas have been discussed and presented by Howard et al (32); however, a detailed description and prescription for a successful implementation is missing.

5.3.4. Integration of Robust Design and reliability engineering

Reliability engineering and design for reliability have a strong tradition especially in the aviation and automotive industry. However, the capabilities and opportunities of Robust Design with all its methods and tools have so far not really been utilized. A suggestion for further research is to investigate into the integration of Robust Design and Reliability engineering but also to find potential synergies between the two. Robustness against time and usage induced variations that result in performance degradation as well as failure is an essential goal for the design of the product.

5.3.5. Economical perspective on variation management

As an extension to the suggested research on a holistic variation management approach and process, investigations into the economical dimension of the problem would be highly relevant. Cost-benefit analyses between the different levers (32) to approach variation in marketing, design and production are especially interesting. The selection of the customer target group and the outsourcing of production can for example have a tremendous impact on how to allocate and evaluate efforts and resources.

5.4.Concluding remarks

This PhD project has been an exciting endeavor with many challenges and joys led by curiosity and the striving for learning new things. It gave me a great opportunity to dive deep into the material of Robust Design, Reliability Engineering and Quality Engineering in general. The project featured an interesting variety of case companies and other side projects alongside the actual PhD project from small start -up companies to global players in the shipping, oil and gas as well as the medical industry.

On a personal note, with hindsight to the time as a practitioner of Robust Design in my previous position in the aviation industry, I only got to appreciate the value of Robust Design to a certain extent. In many cases, Robust Design is seen as a good practice of engineering design or at the other extreme as complex optimization of surrogate models. Robustness in its entirety as quality characteristic is oftentimes underestimated. Of course, a product needs to fulfill its functional requirements, and performance matters a lot, but from a quality point of view having a robust product and system is in many dimensions the key to high quality products: from an easier production and predictable performance and looks to a reliable performance and graceful failure.

Besides the professional and academic learning, taking on a PhD project also promotes the personal development in terms of having a systematic and methodological working approach, self-organization and motivation, abstract problem solving abilities and presentation as well as writing skills.

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Appended Papers

Paper A

Mechanisms and coherences of robust design methodology: a robust design process proposal

Paper B

Robustness Metrics: Consolidating the Multiple Approaches to Quantify Robustness

Paper C

The Contradiction Index: a new Metric combining System Complexity and Robustness for early Design Stages

Paper D

A model-based approach to associate complexity and robustness in engineering systems

Paper E

The Translation between Functional Requirements and Design Parameters for Robust Design

Paper F

The Variation Management Framework (VMF) Tool for Robust Design

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Mechanisms and coherences of robust design methodology: a robust design process proposal

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Although robust design (RD) methods are recognised as a way of developing mechanical products with consistent and predictable performance and quality, they do not experience widespread success in industry. One reason being the lack of a coherent RD process (RDP). In this contribution we analyse commonly used RD methods to identify their mechanisms and coherences and propose a RDP that is connected to the actual design tasks of the design engineer. The presented RDP comprises four main activities: (1) design and modification of the conceptual design solution, (2) measuring and modelling the robustness of the design, (3) processing and evaluation of the robustness data and (4) scaling of the design to optimise parameter and tolerance values. For each of the activities, the set of relevant RD methods is presented. The main objective of the RDP is to provide the design team with a better overview and understanding of the RD toolbox and to support the application of RD continuously throughout the product development by providing a sequential description of when to apply the methods and how they affect the robustness of the design.

Keywords: robust resign; process; product development; variation; implementation

1. Introduction

The reliable and predictable functional performance of products is of crucial importance to companies that develop and produce (mechanical) products. Failures in meeting this can lead to non-satisfied customers, scrap, loss of brand value, product recalls, etc. A recognised way of obtaining a high and consistent level of product quality is through the use of robust design methodology (RDM). Essentially, the aim of Robust Design (RD) is to develop products with an optimised functional performance that is insensitive to variations in the noise factors (NFs) as classically promoted by Taguchi (often referred to as type I RD) and to variations in the product's design parameters (DPs) (type II RD) (Chen, Allen, Tsui, & Mistree, 1996). Especially in early design phases, type II RD plays an important role to ensure flexibility in the design space later on. The IEEE (Geraci, Katki, McMonegal, Meyer, & Porteous, 1991) defines robustness as 'the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environmental conditions' (p. 174). The uptake of RDM in industry is very diverse. Many example cases of applications of RD can be found in the literature (see e.g. Bertini, Credi, Marconcini, & Giovannini, 2012; Kang, Heo, Kim, Choi, & Kim, 2012). Krogstie, Ebro and Howard also describe the successful implementation of RD in four well-established companies (2014). Other studies have shown that various methods that fall into the suite of RD are regularly applied in industry (Araujo, Benedetto-Neto, Campello, Segre, & Wright, 1996; Fujita &

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Matsuo, 2005). Especially tolerance design is a very common method to ensure functional robustness (Chase & Parkinson, 1991). However, surveys conducted in the UK, Sweden and USA suggest that both in terms of knowledge and usage the concept of RD is still not experiencing widespread success (Araujo et al., 1996; Gremyr, Arvidsson, & Johansson, 2003; Thornton, Donnelly, & Ertan, 2000). The lack of a RD process (RDP) – *a coherent approach structuring and arranging all individual methods in the RDM landscape* – has been reported to be one reason (Krogstie et al., 2014). Seen from the design engineer's point-of-view, an extensive toolbox is provided by the literature, but it is relatively unclear how the methods are connected, in which order they should be used and how to transfer the mind-set of RD into an ordered set of activities. However, the current research streams do not seem to address this issue.

This contribution has two objectives. Firstly, to clarify the mechanisms of RD: that is, what are the mechanisms of the available RD methods? Secondly, to find coherences between the methods, and identify how these relate to the activities of the design engineers and propose a coherent RDP. The RDP shall be a 'next step' guide on where the single tools can be positioned. It should fulfil the following requirements:

Req 1: The process should house all RD methods.
Req 2: The process should provide a sequence of use of all RD methods.
Req 3: The process should link to the activities of the design engineers.

Robust Design is a method and tool-driven field. To reach the objectives, we therefore analyse methods commonly associated with RD to derive how they work. We then describe their coherences and propose a RDP based on general design activities, which supports the design engineer's pursuit of a robust design throughout the product development process (PDP). The application of the RDP in specific contexts is out of scope for this study. Figure 1 summarises the methodology.

It is the intention that the RDP should be applicable in all design stages and that it can be used not only as an analysis toolbox, but rather act as a complete framework containing synthesis tools as well. The underlying assumption for this study is that the RDM can be represented by its methods and tools. Due to the authors' background in mechanical engineering the focus is mainly on the RD of mechanical products.

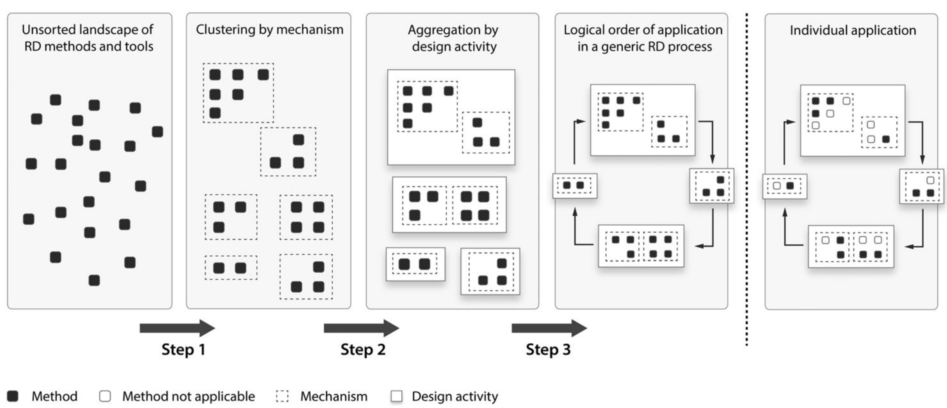

Figure 1. Deriving the RDP.

The outline of the article is as follows. In Section 2 we present a literature study on the most recent research in the field of RD to get an idea of current research streams in that area and if the identified issues regarding the application of RD in industry are being addressed. In the proceeding chapter we analyse the methods and tools commonly associated with RD and elaborate on the applicability of available processes and frameworks followed by our proposal of the RDP. The article closes with a discussion and a conclusion.

2. Current research in RD

RD has been subject to numerous research projects and has therefore also led to many publications in the past decades. To judge current trends within the field, recent publications since 2010 have been reviewed. The Google Scholar search engine has been used to extract 80 relevant papers. The selection of relevant papers was done by screening of the titles and abstracts and solely based on the authors' opinion about the papers' relevance to RD. The selection is comprehensive but selective.

2.1. *RD methods*

RD has its origins in Taguchi's ideas of quality loss occurring with any deviation from the target performance and the so-called Taguchi method consisting of System, Parameter and Tolerance Design (Taguchi, Chowdhury, & Wu, 2005).

Recently, Ebro, Howard, and Rasmussen (2012) promoted the use of Kinematic Design and Design Clarity to ensure the right number and way of constraining parts in an assembly for an improved System Design.

However, the largest share of recent publications deals with RD Optimisation (RDO). RDO is directly related to Taguchi's Parameter Design where experimental data and the signal-to-noise ratio (SNR) are used to measure and optimise the robustness of single functions. Eifler et al. (2011) and Hutcheson and Mcadams (2012) present further sensitivity measures and indices to quantify robustness. Yadav, Bhamare, and Rathore. (2010) and Yang and Du (2014) utilise the total quality loss as cost function in the optimisation to account for multiple objectives. Other scholars, such as Saha and Ray (2011), focused on the improvement of the efficiency and performance of the optimisation algorithms themselves. Another stream within RDO is reliability-based RDO (RBRDO) and probabilistic RD taking the uncertainties and the probability of the occurrence of variation into account to optimise the robustness and reliability of products as opposed to the deterministic original approach by Taguchi. Many contributions on novel and improved algorithms for RBRDO can be found in the recent literature (see e.g. Steenackers, Versluys, Runacres, & Guillaume, 2011; Tang, Chen, & Wei, 2012; Shahraki & Noorossana, 2014). Lijuan, Jun, and Yu (2011) propose a method to integrate RD, Axiomatic Design and reliability-based design to improve the efficiency of the optimisation. Various case studies on RDO were conducted. Among those are, for example, the robust optimisation of a low-pressure turbine of a jet engine and a suspension system (Bertini et al., 2012; Kang et al., 2012).

The simulation and prediction of geometric variations for assemblies is another research field within RD that is related to Taguchi's Tolerance Design. Schleich, Walter, Wartzack, Anwer, and Mathieu (2012) use skin models to incorporate manufacturing data to increase the detail and accuracy of geometric variation simulation. Other studies seek to extent geometric variation simulations by, for example, including the influence of welding on the final assembly (Pahkamaa, Wärmefjord, Karlsson, Söderberg, &

Goldak, 2012) or by regarding deformable, slender parts such as cables and hoses (Hermansson, Carlson, Bjo, & Soderberg, 2013).

2.2. *RD frameworks*

Apart from the mentioned research on RD methods, some recent publications deal with the general organisation and framing of RDM to increase the understanding and the efficiency of the application. Howard et al. (2014) proposed a framework to structure RD efforts, introducing a mapping of the influences of variation from the production all the way to the customer perception of the final product. Göhler and Howard (2014) introduced a way to classify tools and methods associated with RD to clarify their purposes for a more efficient application.

2.3. *Application of RD in industry*

Other recent studies looked at the use of RD in industry. Gremyr and Hasenkamp (2011) investigated the application of RD (especially design of experiments) in a medium-sized Swedish company. They found that RDM tools are applied regularly but that 'the principle of insensitivity to noise factors has not fully permeated the general way of thinking' (p. 56) and therefore hindered the optimal use of the tools. Fazl Mashhadi, Alänge, and Roos (2012) and Fazl Mashhadi, Alänge, Gustafsson, and Roos (2015) studied the introduction of RD at Volvo. The first attempt of 'tool-pushing' by management did not find acceptance and failed. Based on the experiences, a second initiative was developed founded on 'practice-pulling through local learning processes in the organization', which turned out to be successful.

The literature review on recent publications associated with RD suggests that current research activities mostly focus on the improvement and extension of RD methods – especially RDO in various forms. Deterministic and probabilistic optimisations taking the reliability perspective into consideration contribute with a large proportion of the latest publications. Case studies on robust optimisation constitute another large share of the publications. Generally speaking, the current research streams within RD are rather method dominant and do not address the issue of implementation and application of RD in industry. Only 5 of the 80 reviewed papers deal with framing RDM or the application of RDM in industry. There is still a lack of a coherent and structured RDP putting available and established as well as new methods into context and thereby easing the application in industry.

3. Analysis of RD methods

In this section we analyse common RD methods and tools to derive their mechanisms and working principles. The goal is to establish a common base to evaluate existing frameworks and processes in the area of RD against the requirements of a coherent RDP as defined in the introduction.

3.1. *Selection of tools*

There are numerous tools and methods being used in product development to support the design engineers in their work covering various fields within the Design for X spectrum. For this investigation, only the tools and methods commonly associated with RD were taken into account. However, some of them are not exclusively RD tools but are also used in other contexts and fields not focusing on reducing sensitivities and functional variation. The tools were selected from four sources.

(1) RD methods in industry

To reflect the actual application of RDM in industry, four large companies in product development and engineering consultancy were asked to share their RD tool boxes. The companies are not representative but were chosen for their rigorous implementation and application of RDM. The aim of this contribution is neither to compare different tool boxes nor their frequencies of use. This short survey shall rather give an idea about which methods are actually being used and ensure their capturing in the derivation of the RDP.

(2) RDM reviews and surveys in literature

To consider a wide range of different methods and tools, the list from (1) was augmented by additional tools extracted from the RD literature. Existing reviews and classifications of RD methods were used as sources (Eifler, Ebro, & Howard, 2013; Hasenkamp, Arvidsson, & Gremyr, 2009; Matthiassen, 1997). Furthermore, methods mentioned in surveys about the industrial use of RD in various regions of the world were also included (Araujo et al., 1996; Gremyr et al., 2003; Thornton et al., 2000).

(3) RD special interest group (SIG) workshops and surveys

The RD SIG ran workshops and surveys on the ICED13, Design14 and ISoRD14 conferences asking participants from academia and industry to name and place RD methods and tools they actively apply.

(4) Authors' experience

The authors have worked as RD consultants and as development engineer within an aerospace company, totalling 15+ years of experience working with applied RD and therefore have hands-on experience with many of the RD methods.

3.2. *Delimitation*

Any given body of methods will be surrounded by somewhat related methods. Therefore a delimitation of the field is necessary. We follow our working definition of RD methods as stated in the introduction. Some methods that are often mentioned in the RD literature do not fall into this category and are therefore excluded from the process model. These include the following.

3.2.1. *Methods for identifying customer and functional requirements*

Although the starting point for an analysis of the robustness of a design would typically be the identification of the functional requirements, this is regarded as out-of-scope in this context, as requirements management is regarded as a separate topic typically carried out by other people than the design engineers, which are the target audience for this publication. Therefore, methods such as quality function deployment (QFD), voice-of-the-customer (VOC), etc. are not included in the process model.

3.2.2. *Methods relating to reliability and risk management*

In a design project, there are numerous risks that can affect the performance of the product and the project: disturbances in the supply chain, misuse of the product, components being mixed up or forgotten during assembly, etc. All entail a risk, but can be said to be out of the hands of the design engineer, that is, these risks have to be dealt with by other people and by other means than changing the features of the design. Furthermore, although failure modes and effects analysis (FMEA) and fault tree analysis (FTA) are often mentioned in literature as belonging to the suite of RD methods, it is the opinion of this research that they do not belong there.

Table 1 lists commonly used RD methods and tools in alphabetical order, including short descriptions. The list is not complete but comprehensive from the authors' point of view.

3.3. *Mechanisms and working principles of RD methods and tools*

As shown in Figure 1 step 1, it is our goal to increase the understanding of the inherent mechanisms and working principles of the RD methods and tools to, then in the next step, be able to assign them to specific activities of the engineer. A way to describe how RD methods work is through the model of the transfer function (TF). The TF is the mathematical description of the functional performance dependent on the influencing parameters (usually in the form $f = f(x_1, \ldots, x_n)$). Although methods have different names and may have minor differences in the way they are described or applied, they can ultimately be categorised based on how they affect the TF. Using the TF as a reference to analyse each of the RD methods listed in Table 1, eight different independent mechanisms related to RD have been identified. In the following, the identified mechanisms of the RDM, that is, the interactions of the methods with the TF and therefore the robustness of the design, are described. The results are summarised in Table 3.

3.3.1. *Robust concept design*

Following design guidelines and best practices can influence the robustness already in the conceptual stage. The selection of the working principle and the conceptual system design solution can have a major effect on the robustness of the concept and subsequently the final design. Taguchi et al. (2005) as well as Andersson (1996) stress the importance of system design, especially conceptual design. Generally, different working principles yield very different system and function responses, that is, TFs, and can therefore differ greatly in terms of robustness against variation.

3.3.2. *Reduction of couplings between functions*

In the case of a multi-function design, it is likely that different functions share the same influencing parameters – so-called DPs. The functions are therefore said to be coupled. However, the functional response and also the sensitivity towards the DP can be very different or even contradicting. Also, the DP's target values and design ranges differ in most cases which makes trade-offs necessary compromising the overall performance. The Independence Axiom (Axiom 1) of Suh's Axiomatic Design (2001) addresses the coupling of functions and its implications. He proposes to un- or decouple the functions from each other to obtain independent functions that can be adjusted by a set of DPs that do not interfere with other functions. Matthiassen (1997) describes the differentiation and separation of functions as means to avoid compromising the performance due to conflicting or contradicting demands (functional requirements).

Table 1. List of commonly used methods in RD.

Methods and tools	Short description	Industry RD toolboxes	RDM reviews/ surveys	RD SIG workshops	Authors' experience
1. Analytical TF modelling	Usage of analytical mathematical expressions to (simplify and) model functional responses		✓		✓
2. Axiomatic design Axiom 1	Striving for the independence of functions (decoupling, uncoupling) can yield robustness		✓	✓	✓
3. Axiomatic design Axiom 2	Maximisation of the probability of fulfilling the functional requirements by reducing the number of influencing factors and designing to process capabilities		✓	✓	
4. Design clarity	Design for unambiguous interfaces and force transmission	✓	✓	✓	✓
5. Design matrix	Linear mapping between functional output and DPs in matrix form				✓
6. DoE	Statistically designed experiments to maximise information and minimise number of required experiments	✓	✓	✓	✓
7. DSM	Matrix representation of structures and correlations in complex systems				✓
8. Error transmission formula	Calculation of the variance of a function utilising sensitivities and variances of the influencing factors		✓		
9. Ishikawa/Fishbone diagram	Systematical decomposition of influencing factors to a function in a fishbone-like graphical representation	✓	✓		✓
10. Kinematic design	Design for ideally constrained mechanisms	✓	✓	✓	✓
11. Locating schemes	Design for ideally constraining all 6 degrees of freedom in assemblies	✓	✓	✓	
12. Monte Carlo analysis	Statistical evaluation of repeated model simulations based on random sampling of input parameters following predefined probability distributions	✓	✓		✓
13. Optimisation of transfer function or SNR	Derivation and optimisation of cost functions relating to functional performance and variance	✓	✓	✓	
14. P-diagram	Graphical representation of a function or process	✓	✓		✓

(*Continued*)

Table 1. Continued.

Methods and tools	Short description	Industry RD toolboxes	RDM reviews/ surveys	RD SIG workshops	Authors' experience
	distinguishing between (1) signal/input factors, (2) control factors, (3) NFs and (4) output				
15. Pareto analysis	Derivation and ranking of most influencing factors towards a functional output		✓		✓
16. Response surface methodology and other data fitting methods	Statistical fitting of a surrogate model to experimental data	✓	✓		
17. Safety factors wrt. structural properties and process capability data	Include safety factors to account for variations and uncertainties	✓	✓	✓	✓
18. Selection of robust working principle and conceptual design solution	Inherently more robust working principles shall be exploited	✓	✓	✓	✓
19. Sensitivity analysis	Assessment of sensitivities of functions to variation in single or multiple parameters	✓		✓	✓
20. Separation/integration	Separation/integration of functions to reduce functional variance	✓	✓		✓
21. Tolerance chains	Derivation of the influence of tolerances on resulting gaps or overlaps in assemblies. Strive for short tolerance chains to reduce variation of the gap or overlap	✓	✓	✓	✓
22. Tolerance management	Optimisation of tolerance allocations to reduce functional variation and cost	✓	✓	✓	
23. Variation mode and effects analysis	Subjective quantification of the occurrence and impact of variation on the functional performance		✓	✓	

3.3.3. *Reduction of number of influencing factors*

A product's functions are defined by the correlation of DPs and NFs to the function response or output. The model of the TF captures all of these influencing factors. In the light of robustness, that is, variability, of the functional response, all the influencing factors contribute with their variation. Assuming the independence of the DPs and NFs and a normal distribution, the Taylor Series expansion gives

$$\sigma_f^2 = \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i} \right)^2 \sigma_i^2,$$

where σ_i and σ_f are the standard deviations of the *i*th influencing factor and the functional performance, respectively. As a result, the total possible variance of the resulting functional output increases with the number of influencing factors (or remains the same at best). Suh (2001) describes this with the Information Axiom (Axiom 2 in Axiomatic Design). The probability of fulfilling the functional requirement is inversely proportional to the information content. In other words, the lower the information content the higher the probability of achieving the desired functional response. Many researchers, including Pahl, Beitz, Feldhusen, and Grote (2007), Matthiassen (1997) and Mørup (1993), elaborated over the use of design guidelines and principles to ultimately lower the number of influencing factors for an increase in predictability and robustness. Examples are to avoid long tolerance chains, utilise self-adjustment, unambiguous loading and many more (22 in total). The tools of Location Schemes, Design Clarity and Kinematic Design facilitate the principles of ideally constrained interfaces and mechanisms and, hence, reduce the number of influencing factors, to obtain unambiguous force flows (Ebro et al., 2012; Söderberg, Lindkvist, & Carlson, 2006).

3.3.4. *Design with robustness margins*

A common and widely used approach especially in the first iteration loop of product development is to build in margins. This might be costly in the way that the design is over-dimensioned; however, margins do not only cover uncertainty in the calculations and assumptions but also uncertainties in production and use, hence robustness. Typical and established margins are structural safety factors, where, for example, the maximum allowable stress or strain is a factor smaller than the actual material properties in order to allow for variation.

3.3.5. *Measuring of system response*

The measuring of robustness represents a large fraction of the RDM. The central point is the measurement of the system or function response in the design space and how it changes due to a change in one or more of the DPs and NFs. Simple one-factor-at-the-time screening procedures become costly very quickly for an increased number of experiments or simulations due to changing parameters and levels and do not capture interaction effects. Structured planning of experiments and simulations helps exploring the design space in an effective and efficient manner. Design of experiments (DoE) has its roots in the 1920s starting with work from Fisher and reaches up to today (Antony, 2003). Taguchi operationalised orthogonal arrays, which were further developed by Welch, Yu, Kang, and Sacks (1990). The data gained from the experiments (testing) and simulations build the backbone for empirically derived TFs.

3.3.6. *Modelling of system response*

The prediction and optimisation of the system or functional response requires the formulation of a model, that is, a TF. The TF can be derived from measurement data or simulation results by fitting (regression modelling) a polynomial or other mathematical functions to the data. The Response Surface Methodology by Box and Wilson is one of the well-established ways to derive the TF from big data sets (1951). In some cases the TFs can also be derived analytically. In Axiomatic Design by Suh, design matrices are derived for the TFs and the mapping between the functional and physical domain (Suh, 2001). However, the matrix form bears the disadvantage of linearity and is hence not suitable for most real design problems. An alternative, more simple and qualitative way of deriving a TF is by using variation modes and effects analysis (VMEA), which is essentially an estimation of the system response based on experience from previous designs.

3.3.7. *Processing and evaluation of system response*

Several methods and tools in the RDM can be applied to evaluate the robustness based on the mathematical formulation of the system response. The two types of outputs are metrics and visualisations, where the visualisation can be quantitative based on the metrics or qualitative.

Metrics: Sensitivity values and ratios for single or multiple DPs or NFs can be derived from the gradient of the TF or by utilising sensitivity analyses. Estimated yield rates and variances of the functional outputs can be calculated utilising Monte Carlo analysis or the error transmission formula. The SNR expresses the relative magnitude of the variation compared to the intended performance.

Visualisations: The plotting of the TF with respect to one or multiple DPs or NFs is one way of visualisation. Qualitative representations like in Fishbone and P-Diagrams where the influencing factors, but not their contribution and sensitivities are captured are very common in the RDM. Also matrix-based representations such as design structure matrices (DSMs) can help visualise the relations between functions and DPs or the coupling of functions. Pareto-analyses are often used to visualise the sensitivity of the individual DPs quantitatively.

3.3.8. *Scaling of DPs*

The function response to the DPs is often nonlinear. That suggests that there are settings of the DPs that minimise the variance of the functional response. Most designs cannot be idealised to an uncoupled or decoupled design with only one main DP for each function. Realistic design problems tend to be more complex integrating a lot of functionality. To find a RD despite of couplings, restrictions and constraints, it is desired to scale all DPs in a way that the nominal functional response is met but also the variance is minimised. The TF itself (e.g. in the form of a response surface model) and the SNR as used by Taguchi can be utilised to optimise the DPs for target and variance of a function's output. In the Taguchi method, this stage is called Parameter Design (Taguchi et al., 2005). Other researchers have developed other cost functions to optimise the design's robustness. Tolerance management is a more and more integral part of the RDO.

4. RD processes and frameworks

In the literature, different descriptions of method classifications, frameworks and processes related to RD can be found. RD was first introduced by Taguchi in the 1950s. The so-called Taguchi method was the first framework incorporating the ideas and mind-sets of RD and is still used in developing companies. Taguchi distinguished between three main phases of RD: (1) the system design which corresponds to concept and embodiment of a design solution addressing the functional requirements of the product, (2) the parameter design phase in which the design is optimised for robustness – designed experiments are used to gain understanding about the system behaviour and the sensitivity of DPs and NFs, followed by the actual optimisation of the SNR and (3) the setting of tolerances optimising the design with respect to manufacturing costs (Yang, 2007). The Taguchi approach focuses on type I RD to optimise the robustness against NFs utilising systematic experimentation following orthogonal arrays in the parameter design phase. System design and tolerance design play a less important role since Taguchi sees them as 'specialist's territory' and last 'countermeasure' to ensure a robust performance, respectively (Taguchi et al., 2005).

In recent years, design for Six Sigma (DfSS) has become relatively successful in industry (Goh, 2002). The mind-set of DfSS is similar to the approach found in the Six Sigma paradigm of continuous improvement. But where Six Sigma is aimed at improving an existing *process*, the objective of DfSS is to design a reliable *product* from the ground-up (Creveling, Slutsky, & Antis, 2002). In DfSS, the approach is typically called IDOV (or something similar) comprising a series of steps each containing suggested methods. The IDOV steps are (1) **I**dentify customer and product requirements using, for example, QFD and VOC, (2) **D**esign conceptual solutions and identify risks using, for example, FMEA, (3) **O**ptimise the design using process capability information, RD methods, Monte Carlo simulations and tolerance management and, finally, (4) **V**alidate the design by testing and reviewing, using, for example, highly accelerated lifetime tests, reliability engineering and FMEA. DfSS is meant to be a comprehensive 'concept aiming at Six Sigma performance by improved design activity' (Hasenkamp, 2010, p. 317) to give a high-level guidance for quality and reliability activities of a developing company. However, RD is only seen as a subset of this as part of the Optimise step and although it is not described in great detail it is noticeable that it is seen as a late-stage analysis and optimisation of the design.

Other frameworks associated with RD deal with variation management. Variation risk management (VRM) proposed by Thornton is one of them (2004). VRM is a framework to structure efforts to reduce risks caused by variation. It includes 22 industry practices that are applied in 3 general stages. (1) The risk identification stage, where a system of so-called variation risk factors is created. This includes the identification of key characteristics (KCs) in a risk flow down manner comprising four levels: Product KCs, Sub System KCs, Part KCs and Process KCs. (2) The risk assessment with two general approaches – one being the prediction of the final quality by summing up all individual process variations. The second one utilises a top-down approach allocating allowable variation to the single features in the form of tolerances. In that approach the assigned tolerances are compared to the predicted process capability (Cpk) values to predict the final quality. The risk assessment builds upon the variation modelling, the feedback of production capabilities and the estimation of capability uncertainty. And (3) the risk mitigation through design changes and process improvements. This includes the practices of cost/benefit trade-offs, RD and manufacturing quality plans. For RD, Thornton refers to the Taguchi method. The VRM framework addresses the entire variation problem, including ingoing variation, that is, the capability of the production processes as well as the sensitivity of the design to variation. In VRM, RD is seen as part of the risk mitigation activities. VRM focuses more on the production side and on allocating parameter variation and predicting functional variation, than supporting the design engineer in the effort of designing an inherently robust design by changing the geometry and features of the design.

Hasenkamp et al. (2009) made an attempt to frame the RDM answering the questions: Why should RD be used? What should be done and how should it be done? They distinguish between (1) principles, (2) practices and (3) tools of RD. As principles they mention 'Awareness of Variation', 'Focus on the Customer' and 'Continuous Applicability' explaining the overall mind-set of a continuous focus on variation. Practices give a high-level, fundamental input on how robustness can be achieved and cover design rules, insensitivity to NFs and robust optimisation. The actual RD activities and methods are summarised in tools including mainly analysis tools such as VMEA, P-Diagram, TF and DoE in an unstructured manner. Fazl Mashhadi et al. (2015) extended the framework based on their experiences in industry. The main aim of this framework is to convey the goal and mind-set of RD facilitated by certain practices and tools to assist the implementation, acceptance and application of RD in industry.

Göhler and Howard (2014) provide a more detailed classification of RD methods, categorising the methods based on the objective or purpose of applying them. The methods are classified as supporting one or more of the four categories: (1) RD principles, (2) RD evaluation, (3) robustness optimisation and (4) robustness visualisation. These categories are not stitched together to a coherent process, but shall rather give practitioners a guidance and understanding of what certain methods in RD are used for and what they can deliver.

The axiomatic design framework by Suh introduces two axioms, namely the Independence and the Information Axiom. The main idea is to reduce the coupling of functions in a design (independence of functions) and to strive for minimised information content. The robustness of a design is measured with the probability of fulfilling all functional requirements simultaneously. This probability is inversely proportional to the information content (Suh, 2001). In practice this framework can be seen as design guideline which provides heuristics for a good and RD.

Howard et al. (2014) propose the Variation Management Framework (VMF) for RD. It maps the variation of production variables through transfer and quality loss functions to the customer satisfaction of the product on the market. The VMF is a simplification of the mapping of variations through the production, design and customer domain. It has its strengths in the simple and easy description and visualisation of the need and influence of RD.

4.1. *Gaps in existing frameworks*

The presented frameworks pursue different objectives in framing and prescribing RD. Their main shortcomings are discussed below and summarised in Table 2:

- Lack of low-level guidance and connection to design activities of design engineers.

From the review, we found that the majority of frameworks and processes address managerial and organisational or theoretical and academic aspects of RD. The frameworks provide a high-level overview of how RD fits into the overall development process. But seen from the design engineer's or project manager's point-of-view, the frameworks do not provide detailed guidance on the specific activities of RD or are very focused on single methods (like Taguchi method and Axiomatic Design). In DfSS, VRM and VMF, RD is merely a subset of the overall framework and not described in great detail. The lack of understanding of applicability of the methods and their coherences is not addressed. Further, there is no prescribed sequence for the application of RDM.

- Synthesis tools missing.

Another finding is that most of the frameworks do not address the whole landscape and mechanisms of RD as identified in Section 3. The synthesis part is often neglected and RD is mainly seen as an analysis and optimisation tool, that is, the frameworks provide methods that can be used to analyse the current level of robustness and optimise it within the constraints of the given concept, but they do not provide any guidance for the design engineer at the *point-of-design*, that is, during the actual sketching and modelling. As a consequence, the final design may simply end up as being a sub-optimised version of the initial concept, rather than an inherently robust concept, based on guidelines and principles for obtaining robust concepts. This is especially unfortunate, since the actual measuring and modelling of the robustness can be challenging and costly.

- Unordered and unsorted list of RD methods.

The frameworks describe an array of relevant methods, but do not go into details about which order to apply the tools in and what the objective of the individual tool is. A coherent RDP is lacking. The foci and objectives of methods are often missing leaving the practitioners with a potentially overwhelming toolbox.

5. Proposing a RDP

As outlined earlier in this paper, although broadly acknowledged, the current uptake and application of RD in industry is rather unsatisfactory. One reason being the gap between academic research and the practical application in industry. Another reason is the fuzziness of the RD toolbox with no coherent RDP as identified in the previous section.

5.1. *Derivation of a RDP*

The assumption behind the proposal of the RDP is that a process is inherently built and structured by the activities and methods it comprises. Reversing the argumentation, the coherences of the methods and activities form the process.

The eight mechanisms of RDM give a semi-structured description of the RD toolbox. However, from the design engineer's point of view, it is not always clear how the methods fit into the everyday activities in a development project. The engineer is shifting back and forth between synthesis and analysis on both conceptual and detailed design levels and therefore the RDP should support this way of working. The RDP should, furthermore, addresses the requirements as stated in the introduction: (1) housing of all RD methods, (2) provision of an application sequence and (3) linking the RD methods to the activities of the design engineers. Table 3 summarises the results from the previous section and connects the methods to the design activities of the engineer.

Table 2. Summary of existing RD frameworks.??

	Categories of RD methods and tools								Target group				
Framework	Robust concept design	Reduction of couplings between functions	Reduction of number of influencing factors	Design with robustness margins	Measuring of system response	Modelling of system response	Evaluation of system response	Scaling of design factors	Engineers	Managers	Prescribed sequence	Supplies motivation of application	Links methods to design activities
Taguchi	✓				✓	✓	✓	✓	✓		✓	✓	✓
DfSS			RD is a subset and not specified further							✓	✓		
VRM			RD is a subset and not specified further							✓	✓		
Hasenkamp	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	
Göhler	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Axiom.Des		✓	✓		✓	✓	✓		✓	✓			
VMF				RD is a subset and not specified further						✓			

Table 3. RDM mechanisms and engineering activities.

No	Mechanisms of RDM	Tools/methods	What the designer does (design activities)
I	Robust concept design	Selection of the working principle and the conceptual design solution	1. Conceptual design In this context, conceptual design is understood as defining a new solution to a design problem, as opposed to scaling (see below)
II	Reduction of couplings between functions	Axiomatic design Axiom 1 Separation/integration of functions	
III	Reduction of number of influencing factors	Axiomatic design Axiom 2 Design clarity Kinematic design Locating schemes Tolerance chains	
IV	Design with robustness margins	Safety factors wrt. structural and process capability data	
V	Measuring of system response	DoE	2. Data collection (measuring) and modelling of the system response
VI	Modelling of system response	Analytical transfer function modelling Design matrix Response surface methodology and other data fitting methods Variation mode and effects analysis	
VII	Processing and evaluation of system response	DSM Error transmission formula Ishikawa/Fishbone diagram Monte Carlo analysis P-diagram Pareto analysis Sensitivities analysis	3. Process and evaluate (graphs, metrics, visualisations and deciding on further actions)
VIII	Scaling (optimisation) of DPs	Optimisation of transfer function or SNR Tolerance management	4. Detailed design and scaling (optimisation) of parameters and tolerances

To derive a RDP the underlying activities that are performed by the design engineers need to be understood (Figure 1 step 2). The analysis of the eight mechanisms revealed four governing activities. Firstly, there are mechanisms that address the actual design of the product: these are robust concept design, reduction of couplings and influencing factors and designing with margins. Other mechanisms aim at the assessment and description of the functional performance (measuring and modelling of system response). Further, the last two mechanisms address the processing of the results and the optimisation which again are two very different activities. In summary, the RD efforts can be grouped in four different design steps: (1) using relevant principles and guidelines for obtaining a robust conceptual design, (2) measuring and modelling the robustness of the design, (3) processing the results and either redesigning (back to 1) or (4) optimising the design. Based on these coherences and design activities associated with the methods of RD presented in this paper, we propose a RDP to describe the RD efforts and its methods and tools in a

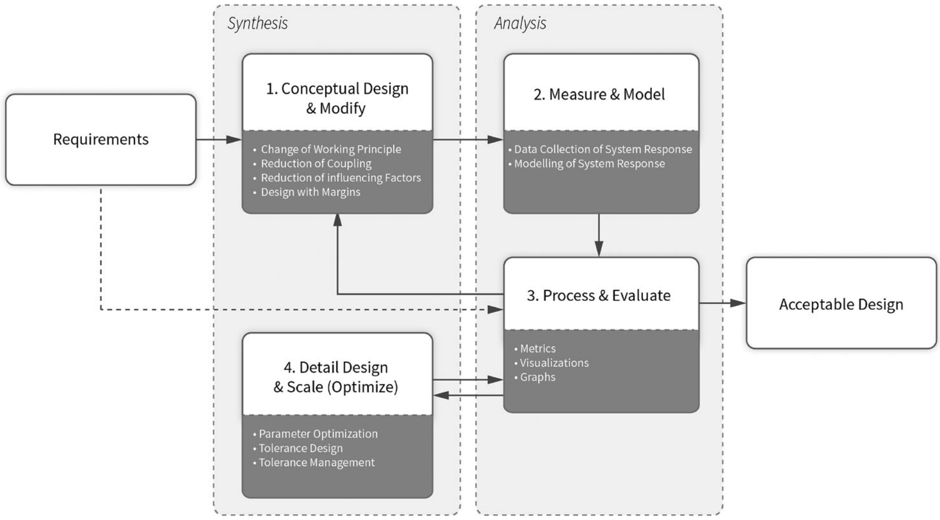

Figure 2 . Robust design process.

comprehensive and structured manner to guide design and development engineers for the application of RD. The nature of the presented activities suggests a certain order and sequence of application, which is shown in Figure 2. The boxes illustrate the design activities; the arrows present the results of each phase that are passed on.

5.2. *The phases of the RDP*

(1) The conceptual design, that is, the creation and further on the modification of the conceptual solution of the design, is the initial phase for the RDP and essential to establish a robust baseline. Activities in this phase change the inherent characteristics of the system response. It entails choosing of an adequate working principle and the obeying of robustness principles and guidelines for each design iteration. Conceptual design decisions as described here do not only refer to the principle design solution on system level (as e.g. in the stage-gate-models) but entail design decisions down to, for example, the selection of a screw over a rivet to connect two pieces of sheet metal. The tools conveying this premise are associated with general engineering experience and lessons learnt from previous designs. This includes the selection of a robust concept, uncoupling the design, reduction of influencing factors and including design margins. Because the next phase – modelling and measuring the robustness of the design – is known to be complex and challenging, it can be an advantage to use sufficient efforts in the conceptual design phase, carefully pursuing a solution that is inherently robust.

(2) The activities in the conceptual phase are logically followed by the application of tools to measure and model the response of the system for nominal values of the DPs and NFs and when subjected to ingoing variations. When seemingly simple designs are coupled or have ambiguous load paths, this step becomes incredibly difficult and time consuming. Some iteration between phase 1 and 2 may be required to produce a clear, unambiguous design suitable for this

phase. The understanding of the system response and the mathematical description is necessary for the evaluation and processing of the data (phase 3) as well as for prediction and optimisation of the design (phase 4).

(3) The third phase comprises the processing and evaluation of the robustness data of the current design. The information can be conveyed in the form of metrics, graphs or illustrations. Checking the results against the requirements gives the basis to decide whether the design is acceptable as is or needs further improvements. This could entail a modification or redesign of the conceptual design solution or a scaling (optimisation) of the existing solution. A re-evaluation of the changed design is necessary to proceed. Note that the evaluation of the market as well as the quality loss associated with variation in functional performance and therefore the setting of functional requirements is not included in the RDP as delimited in Section 3. This information is assumed to be known and available.

(4) In the case that the conceptual robustness has been judged to be satisfactory, the correlations gained in phase 2 can be utilised to optimise the robustness of the design. DPs are scaled to meet the target functional requirements but also to optimise the design for a minimised variance of the overall functional performance.

In a design process, these are recurring activities from the initial sketch to the final design. It is important to note that not all methods and tools associated with the four phases can be or are sensible to be applied in each iteration. Instead it shall be stressed that the proposed RDP gives structured guidance on when, which and how methods can be used and what their underlying mechanisms are.

6. Discussion

When proposing a new process, the usefulness, applicability and interaction with existing processes is of critical importance. In this section we discuss and reflect on some of the most important questions. However, this does not replace a rigorous validation.

6.1. *How would the RDP be applied in a real product development situation?*

Development engineers of any kind face very specific tasks and deliverables every day. Realising what phase of the RDP a given task lays in is of high importance to systematically address the robustness of the product. Are certain phases skipped? Have all options in the conceptual design phase been exhausted to achieve the highest possible level of inherent robustness? Can we go ahead with the measuring (experimentation, prototyping, etc.) and modelling of the system or are there, for example, too many ambiguities increasing the complexity of the model, which are costly and time consuming? The same applies for the processing/evaluation and optimisation phase. Are we sure that the current activity is the most efficient and effective one to achieve the most RD in a given situation? What tools and methods are available for my specific task and deliverable?

Being able to place one's activity in the RDP and selecting an appropriate method enables the engineer to systematically address robustness considerations in the most effective and efficient manner.

From the managerial perspective, the RDP offers the possibility to establish an organised toolbox including only methods and tools appropriate for the company or department.

The selection can be done based on the typical engineering tasks in the context of the product, organisation, expertise, etc. A reduced toolbox with the knowledge about the mechanisms of the individual methods will increase the clarity and therefore the speed and effectiveness of the application.

6.2. *How does the RDP relate to generic PDPs, for example the stage/gate or V-models?*

It is widely acknowledged that product development is an iterative rather than a linear process (Summers & Shah, 2010). Iterative process models like the V-model or agile product development are well established in industry. In practice, certain functions in the product are either reused from previous products or are chosen to be frontloaded to give a proof-of-concept, which makes the development process highly nonlinear. To support this, the RDP is defined in a way that it is decoupled from existing generic development models and it is the intent that the RDP is applicable at any stage of the development process. In agreement with that, work by Hasenkamp, Adler, Carlsson, and Arvidsson (2007) shows that certain RD methods can be used in various phases of a generic PDP.

6.3. *How should RDP be implemented in industry?*

The way of applying RDM in practice varies very much – from non-existent but acknowledged to highly integrated. Also the reasons for application differ from company to company. Krogstie et al. (2014) assessed four companies that have successfully integrated RD. The approaches for integrating RD in their general PDPs differ from robustness metrics for milestones, common understanding in DfSS reviews to specific requests of RD activities by the management and integration into lean processes. The iterative RDP as proposed in this paper covers all these approaches. Studies and experiences have shown that 'tool-pushing' from the management for specific RD tools was unsuccessful (Fazl Mashhadi et al., 2012). The answers to 'Why?' and 'How?' to apply RDM are critical for the understanding of the practitioners, that is, the engineers, and therefore the successful integration. The RDP is therefore thought as a framework for companies to establish their individual RD toolbox and practices. The companies' individual foci are reflected in the model. The assessment and quantification of robustness as well as the visualisation and communication play an essential role in the RD work of these companies.

7. Conclusion

The field of RD includes a wide range of tools and methods. However, a clear process connecting these and supporting the application does not exist. It is still being reported that the integration of RD in industry is not widely spread and that tools and methods for RD are perceived to be too complex and unorganised with no actual guidance for application. This leads to great efforts for implementation, including excessive training and tool pushing rather than a natural pull from the design engineers based on the benefits of using RD.

In this study we analysed 23 methods commonly associated with RD and found 8 underlying independent mechanisms of how these methods work. Based on those, we propose a novel RDP with four main phases covering the actual activities of the design engineer: (1) conceptual design, (2) measure and model, (3) process and evaluate and (4) optimise. The goal is to support the application by clarifying and structuring the use and application of RD methods. Keeping in mind that PDPs are very non-linear in real life as opposed to the descriptions in many academic publications, the nature of the RDP also supports an iterative approach, and is applicable in all design stages. We show that there is a logical sequence for the application and address the applicability to the design engineers. The comparison with RD efforts in the industrial context shows that an application of the proposed process is possible. The RDP is of interest for engineers, lead engineers and management to understand and manage the efforts made to increase, manage and control robustness. Also the training of RD and the creation of company RD Toolboxes can be built upon the proposed framework. The structured and systematic approach to RD by means of a coherent process is needed to increase the uptake in industry.

7.1.Future work

The aim of the RDP proposed in this article is to support the application of RD in industry and provide a better overview and understanding of the RD toolbox. However, the actual usefulness and usability of the process has only been reflected on briefly (Section 6). Validation studies are necessary on project and corporate level. Does the RDP improve the understanding and foster the efficient use of RD methods and tools in practice? To answer that question a study could be run to assess the selection and application of RD methods with and without support of the RDP. On corporate level the benefits of using the RDP could be studied for building a balanced RD toolbox or consolidate and organise an existing one. Another interesting study could be on the integration of quantifiable metrics to steer and measure the robustness of a product.

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Robustness Metrics: Consolidating the Multiple Approaches to Quantify Robustness

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The robustness of a design has a major influence on how much the product's performance will vary and is of great concern to design, quality, and production engineers. While variability is always central to the definition of robustness, the concept does contain ambiguity, and although subtle, this ambiguity can have significant influence on the strategies used to combat variability, the way it is quantified and ultimately, the quality of the final design. In this contribution, the literature for robustness metrics was systematically reviewed. From the 108 relevant publications found, 38 metrics were determined to be conceptually different from one another. The metrics were classified by their meaning and interpretation based on the types of the information necessary to calculate the metrics. Four different classes were identified: (1) sensitivity robustness metrics; (2) size of feasible design space robustness metrics; (3) functional expectancy and dispersion robustness metrics; and (4) probability of compliance robustness metrics. The goal was to give a comprehensive overview of robustness metrics and guidance to scholars and practitioners to understand the different types of robustness metrics and to remove the ambiguities of the term robustness. By applying an exemplar metric from each class to a case study, the differences between the classes were further highlighted. These classes form the basis for the definition of four specific subdefinitions of robustness, namely the "robust concept," "robust design," "robust function," and "robust product."
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Keywords: robust design, robustness, sensitivity, metric, classification, review

1 Introduction

There is much need to clarify the term robustness. While robustness is a property of a design or product that is considered of great importance in many industries, the term robustness will seldom appear in a requirement specification, partly due to its ambiguity, confusion, and misrepresentation. The term has a completely different meaning in common parlance, where consumers will often consider it to be synonymous with strength or durability. In this article, we seek to remove the ambiguity surrounding the technical interpretation of robustness, which is broadly considered by engineers as a property that reduces variability. "Robust Design" (*verb*) is, therefore, a methodology for designing products, devices, and production equipment to perform as intended, despite variation in manufacturing, assembly, material properties, ambient conditions, loading scenarios, or time-related factors [1–3]. Unlike the majority of design and analysis techniques that are based on nominal values [1], Robust Design provides an economical approach to address product quality in complement to the control of manufacturing performance by means of production-focused quality initiatives, such as total quality management, lean manufacturing, or Six Sigma.

While the basic paradigm and the fundamental benefits of robust design are widely accepted by scholars and practitioners, the implementation of a consistent robust design strategy is cumbersome for many organizations [4–6]. Robust design is a very tool/method-centric discipline with vaguely a defined robust design process [7], and as a consequence, only experts know what to apply and when. Furthermore, the term *robustness* is frequently used almost interchangeably with *sensitivity* in a wide range of related, but not clearly delimited research areas, such as sensitivity analysis, computational model building, optimization, etc., [8–10].

A reason for the lack of coherence in terminology is perhaps due to the broad range of robust design activities, from systematic identification of key characteristics [11] through benchmark and comparison of products and processes [2,12,13] to the optimization of robustness and computer-aided tolerancing [8]. Such activities require metrics and indicators that typically differ to suit the activity and are frequently not straight forward to interpret. Previous reviews of robustness optimization techniques indirectly discuss different robustness metrics, however, without reflecting on the different implications of the choice of specific metrics for optimization [8,14–16].

To foster a better understanding of the wide range of available approaches to quantify robustness, this research addresses the ambiguity surrounding the term robustness. The goal of this review is to classify robustness metrics based on their meaning and interpretation.

The remainder of this article is organized as follows. The search criteria and review process for the systematic literature review is described in Sec. 2. In order to organize the metrics uncovered, a theoretical framework is proposed underpinned by the information entities relevant to the basic robust design paradigm in Sec. 3. The unique robustness metrics are then classified and analyzed in Sec. 4, and exemplar metrics from each class are described and applied to a case example to illustrate the differences. In Sec. 5,

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Table 1 Extraction statistic of the systematic literature review

Database	Scopus		Web of Science	
Search strings	Robust design[a] + indicators[a]	"Sensitivity analysis methods" + review	Robust design[a] + indicators[a]	"Sensitivity analysis methods" + review
Total hits	252	38	418	34
Extracted	55	16	36	12
		↓		
Total unique references	90 (Scopus/ISI WoS) + 18 (additional sources)			

[a]Search strings as described in the text.

the verification and validity of the classification scheme as well as the interpretation of the different classes with respect to different facets of robustness are discussed, before concluding the results and the potential of this research in Sec. 6.

2 Systematic Literature Review Process

The quantification of parameter sensitivities plays a large role in almost all scientific fields that use models to describe, analyze, and predict phenomena and synthesize products and systems. As a result, there exist a very large number of scientific manuscripts on sensitivity analysis and metrics with focus on special application scenarios. However, the concept of robustness is not entirely congruent with that of sensitivity. Since these terms are often used as antonyms of one another, a thorough review of the related metrics may help with clarifying the distinction between the terms.

For this purpose, a systematic literature review [17] was conducted to create a comprehensive collection of robustness and sensitivity metrics that can be used in the realm of robust design. The objective of this extraction was to collect as many fundamentally different metrics as possible. Throughout this article the term metric will be used and is unless otherwise stated referring to a measure or quantification of the robustness of a design or product. A review protocol was established prior to the study to ensure a rigorous execution [17].

To establish a general understanding of robustness and sensitivity metrics, six primary publications were reviewed covering sensitivity analysis in general terms [9,10,18] and focused on sampling-based methods [19] as well as sensitivity indices particularly for the use in robust design [13,20]. Based on this initial review, the relevant keywords and search strings for the study were defined as follows:

- robust design, robust engineering, robustness to variation, design for robustness, robust product design, Taguchi, sensitivity to variation, insensitivity to variation, sensitive to variation, insensitive to variation, functional variation
  And
- indicator, indicator" OR "quantifier" OR "metric" OR "sensitivity measure" OR "index" OR "indices" OR "sensitivity information" OR "score"

To include potential metrics outside of the field of robust design but yet applicable for this purpose, a second search for reviews of sensitivity analysis methods in general has been conducted. As sources, the databases of Scopus and Web of Science were selected due to their comprehensive collection of scientific articles relevant to this research. The search was limited to peer-reviewed journal articles to ensure a high level of quality. Furthermore, only publications in the english language and in the field of engineering were considered. The inclusion criteria were the proposal, application, or review of robustness metrics to evaluate the robustness/sensitivity to variation. Excluded were studies on robustness optimization and process capabilities that did *not* specifically describe novel ways and ideas to describe robustness.

For each of the different robustness metrics the mathematical description was taken from the article in order to gain a true understanding of the metric which was less reliant on the authors' terminology or explanation. Overall, the terminology used in the literature is very inconsistent. Every metric was only recorded once by discarding duplicates and minor variations of a metric. A minor variation of a metric would be one which only differs from another metric in the way the normalizing or averaging is conducted for example. Table 1 shows the extraction statistics of the systematic literature review. At the end of the selection process, 90 relevant articles were identified. The list of references also includes 18 additional references that were identified during reading for extensions and clarification of metrics. The review revealed 38 different metrics for robustness (Table 5 in the Appendix).

3 Theoretical Framework

While robustness metrics have a very broad range of applications in all areas, in this article, the review is conducted in the context of product development and engineering design. The classic categorization of robust design methods and metrics has been done differentiating between different types and sources of uncertainties. Historically, there is a distinction made between type I and type II robust design addressing variations in noise factors (uncontrollable) and design parameters (DP) (controllable), respectively [21]. A third type was introduced later by Allen et al. [22] to include variability and uncertainty in the system models. A fourth type was mentioned by Beyer and Sendhof [8] addressing the "uncertainties concerning the fulfillment of constraints the design variables must obey". These uncertainties can further be categorized being deterministic, probabilistic (aleatory), or possibilistic (epistemic) in nature [8]. Aleatory uncertainty is the "stochastic intrinsic variability associated with a physical system or environment." The epistemic uncertainty is related to incomplete knowledge [23].

In this study, the transfer function model (TFM), as described in robust design methodology, was selected as a basis for the analysis of the metrics. The TFM is a means to relate DPs (and noise factors) to the functional performance and is used effectively to promote good design practice in Axiomatic Design [24] and the Variation Management Framework [25].

Figure 1 shows the classical representation of describing the propagation of variation from the physical domain to the functional domain. The different entities are as follows:

(1) *A model or an experiment*. When using a model, the relations within the process need to be understood in order to calculate the robustness, whereas using an experiment treats the process as a black box taking just inputs and output to calculate sensitivities.
(2) *Functional specification limits or quality loss characteristics* defined by the voice of the customer and the business unit's profile for the product.
(3) *Quantified ingoing variation or uncertainty*, such as DP variation, capability data, and variation in use case or noise described in the mission profile (deterministic or probabilistic). The incorporation of epistemic uncertainty bears further challenges to uncertainty modeling utilizing

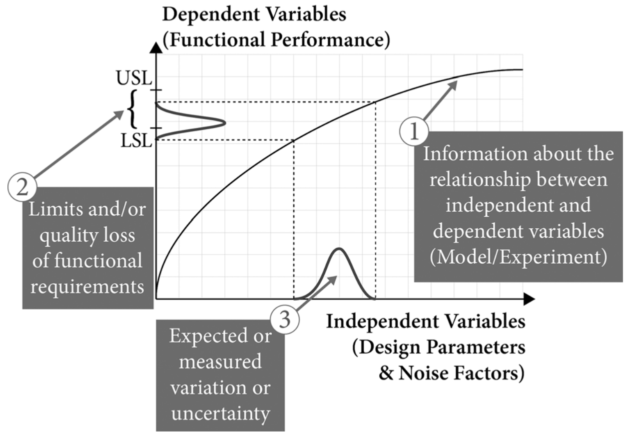


Fig. 1 Robust Design framework

for example fuzzy sets [26,27] and is considered out of scope for this review.

To analyze the robustness metrics, their mathematical descriptions were reviewed with respect to which of the information entities they process (Fig. 1) and what meaning and interpretation of the metrics follow from the TFM.

While the TFM, as seen in Fig. 1, only relates one DP to one functional requirement, it was important to also consider complexity in the analysis, i.e., are single or multiple DPs correlated to single or multiple functional requirements. However, it has to be noted that metrics that are used to take the average, maximum, or minimum of other robustness metrics are not included in the review. The objective analysis of the mathematical descriptions ensured the reliability of the coding for the classification scheme avoiding any ambiguity in classifying the metrics.

The generic scheme for the analysis of the robustness metrics is summarized in Table 2. The results of the analysis of the 38 different metrics identified in the literature review can be found in Table 5 in the Appendix. The findings are complete with respect to the searched databases and generally comprehensive from the authors' point of view.

4 Categorization of Robustness Metrics

The aim of this study is *not* to review and describe each and every metric in depth, since full details of the metrics can be found in the individual references provided. The goal of this study is rather to take a step back to give a classification of a comprehensive collection of robustness metrics in order to address the overall ambiguities of the term robustness and the selection of appropriate metrics as described in the opening of this paper.

Based on the analysis of the metrics (full table of results in the Appendix Table 5), the following classification scheme was derived (Table 3). All of the 38 reviewed robustness metrics could be classified into one of four different classes.

(1) *sensitivity robustness metrics* that quantify the influence of one or more DPs or noise factors (independent factors) to the functional output (see Sec. 4.1)
(2) metrics that describe the *size of the feasible design space* as measure for the robustness (see Sec. 4.2)
(3) metrics that evaluate different *expectancy and dispersion measures* of the functional output (see Sec. 4.3)
(4) metrics that evaluate the *probability of functional compliance* meaning that all functions are satisfactory fulfilled under the influence of ingoing variation (see Sec. 4.4)

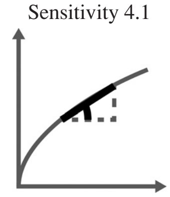
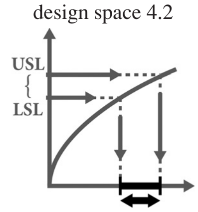
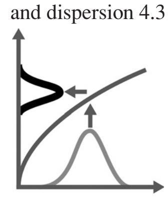
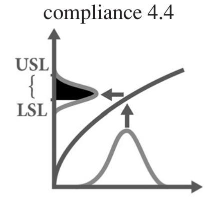
Within each class, the metrics were further analyzed in terms of the level complexity they address:

- robustness of a single function to a single independent variable
- robustness of a single function to sets of independent variables with interactions
- robustness of a system of functions with coupling

Table 2 Analysis scheme for robustness metrics

			Necessary information entities			Level of complexity		
#	Name	Mathematical expression	Model/ experiment	Functional limits	Expected/ measured variation	Independent variables (DPs + NFs) single/multiple	Dependent variables (functional performance) single/multiple	Ref.

Table 3 Classification scheme for robustness metrics

Robustness metric class		Sensitivity 4.1	Size of feasible design space 4.2	Functional expectancy and dispersion 4.3	Probability of functional compliance 4.4
Meaning in the TFM					
Necessary information entities	Model/experiment	✓	✓	✓	✓
	Functional limits	—	✓	—	✓
	Expected/measured variation	—	—	✓	✓
Level of complexity (# of functions/# of independent variables)	1/1	✓	✓	✓	✓
	1/*n*	(✓)	✓	✓	✓
	n/*n*	—	✓	✓	✓

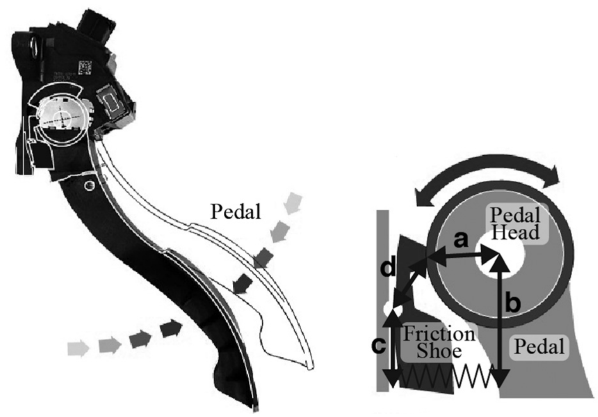


Fig. 2 Schematic diagram of the Toyota gas pedal [28] (Courtesy of Guardian News & Media, Ltd.)

The different classes will be explained in the following, including the application of one robustness metric of each class on the example of the Toyota gas pedal case.

4.1 Example—Toyota Gas Pedal. One of most extensive recalls in automotive history occurred in 2009/10, when the car manufacturer Toyota had to recall several million cars due to an overly sensitive gas pedal which in some instances failed to return after being pressed causing the vehicle to continually accelerate, resulting in numerous serious accidents and fatalities [28]. The mechanism of the gas pedal is supposed to limit the torque required by the driver to hold the pedal in a constant position. This function is realized by a rocker that creates a friction on the pedal head to damp the return moment driven by a spring mounted between the other side of the rocker and the pedal. A simplified description of the problem (Fig. 2) will be used as an example to show the differences between the different classes of robustness metrics.

The return moment M is a function of the dimensions a, b, c, d, s, the coefficient of friction μ_f, and the spring constant k and can be derived using the balance of forces and moments. This gives following simplified expression for the return moment:

$$M = F_{\text{spring}} \cdot \left(b - \frac{c}{d} \cdot \mu_f \cdot a\right) \text{ with } F_{\text{spring}} = k \cdot s \tag{1}$$

M always needs to be greater than zero to ensure a release of the throttle and below 500 N mm to limit the effort for the driver to push the throttle. A second functional requirement shall be the integrity of the friction shoe, where the bending stress σ_b needs to be below the material's yield stress $\sigma_{\max}$ at all times to prevent a failure. A simplified analytical expression for the bending stress can be written as follows, where w and h are the width and the height of the friction shoe, respectively

Table 4 Nominal dimensions and material properties and variation data for the Toyota gas pedal input parameters

	Nominal	Estimated variation (±)	Probability distribution
a	10 mm	0.04 mm	Normal
b	16 mm	0.0483 mm	Normal
c	10 mm	0.04 mm	Normal
d	6 mm	0.035 mm	Normal
k	4 N/mm	1 N/mm	Uniform
s	16 mm	0.1 mm	Normal
μ_f	0.7	0.5	Uniform
w	4 mm	0.03 mm	Normal
h	5 mm	0.032 mm	Normal
$\sigma_{\max}$	50 MPa	5 MPa	Normal

$$\sigma_b = \frac{6 \cdot F_{\text{spring}} \cdot c}{w \cdot h^2} \tag{2}$$

Table 4 summarizes the nominal dimensions and the expected (manufacturing) variation. Note that while the model for the mechanism is an accurate description, the limits and dimensions have been fabricated for example purposes.

4.2 Sensitivity Robustness Metrics. Sensitivity measures play an important role in model building and corroboration as well as parameter prioritization [9]. They also build the simplest form of robustness metric and are a well-established way to relate the change of an independent variable to the change of a dependent variable. In the context of engineering design, this relates to the correlation between DPs or noise factors as independent/input variables to the functional requirements (dependent/output variables). The metrics are based on the evaluation of finite quotients of the form

$$\frac{f(x_1) - f(x_2)}{x_1 - x_2} \text{ or } \frac{f(x+\Delta) - f(x)}{\Delta} \tag{3}$$

For the limit of the interval $\Delta \to 0$, the latter expression yields the formal definition of the derivative of a function f toward a variable x (Eq. (4)). In the case of multiple independent variables, it becomes the partial derivative (Eq. (5))

$$\mathrm{f}'(\mathrm{x}) = \lim_{\Delta \to 0} \frac{f(x+\Delta) - f(x)}{\Delta} \tag{4}$$

$$\frac{\partial f(X)}{\partial x_i} = \lim_{\Delta \to 0} \frac{f(x_1, \ldots, x_i + \Delta, \ldots, x_n) - f(X)}{\Delta} \tag{5}$$

The robustness metrics in this class are either point or range based, which induces certain assumptions and limitations that shall not be further discussed here. There are numerous ways to normalize the metrics to make the measures comparable between different functions and variables.

A simple example for this category is the nominal-range sensitivity (NRS) metric. For the gas pedal example introduced earlier, the metric yields 2.6 for the dimension d with a 5% variation interval (Eq. (6)).

$$\mathrm{NRS}_d = \frac{\dfrac{k \cdot s \cdot \left(b - \dfrac{c}{d \cdot (1+0.05)} \cdot \mu \cdot a\right)}{\mathrm{M}_{\text{nominal}}} - 1}{0.05} \approx 2.6 \tag{6}$$

The NRS describes the amplifying or damping effect of a parameter toward a function. In this case, a variation in the dimension d leads to a relative change in the return moment that is ~2.6 times larger than the ingoing variation for d.

Sensitivity robustness metrics are independent of accurate (realistic) information about variation in the independent variables (information entity 3 Fig. 1). However, range-based metrics require bounds for the evaluation which are in some cases taken from the expected variation but don't have to be. Also, no information about requirements (functional limits) is necessary (information entity 2 Fig. 1).

Sensitivity robustness metrics usually evaluate the robustness of one function with respect to one independent variable (DP or noise factor). The coefficients in linear regression modeling which belong to this class of robustness metrics can (in a limited fashion), however, also be derived for interaction effects with multiple independent variables. There are no metrics in this category addressing multiple functions other than taking the minimum, maximum, or any kind of average neglecting interaction effects.

Summary:

Necessary information entities			Level of complexity (# of functions/# of independent variables)		
Model/ experiment	Functional limits	Expected/ measured variation	1 / 1	1 / n	n / n
✓	–	–	✓	(✓)	–

4.3 Size of Feasible Design Space Robustness Metrics. This class of robustness metrics is based upon the evaluation of the *size of the feasible design space*. The metrics require in addition to information about the relationship between independent and dependent variables (information entity (1)), the functional limits (information entity (2)). They, therefore, put sensitivities into perspective to the requirements on the associated function. Functions can be extremely sensitive when evaluating robustness using the measures presented in 4.1 but yet could be robust in the sense that the requirements on the associated function are rather loose.

Two principles are behind the robustness metrics in this class. The first addresses the question of how much variation (across all independent variables) can be allowed ensuring that the function will always be within the limits, i.e., what is the closest "distance" to the most constraining limit?

The second principle is measuring the entire feasible design space as a metric for robustness. This relates to a distance, area, volume, and polyhedron volume in 1D, 2D, 3D, and nD, respectively. The first principle is dependent on the nominal configuration and reflects a pessimistic approach; the latter is independent of the nominal and reflects an averaging approach to measure robustness. *Size of feasible design space robustness measures* is generally independent of information about the variation in the ingoing parameters. However, metrics like the Mahalanobis distance [29] use variance–covariance matrices to also address the likelihood of violating a constraint. In that case, the distance is scaled with the magnitude of the variance and covariance.

In the one-dimensional case that the size of the feasible design space is to be derived for one independent variable x toward one functional requirement $f(x)$ with an upper and lower specification limit, the calculation reduces to the trivial expressions:

1) Robustness radius:

$$r_R = \min(|(x|f(x) = f_{\max}) - x_{\text{nominal}}|; |(x|f(x) = f_{\min}) - x_{\text{nominal}}|) \tag{7}$$

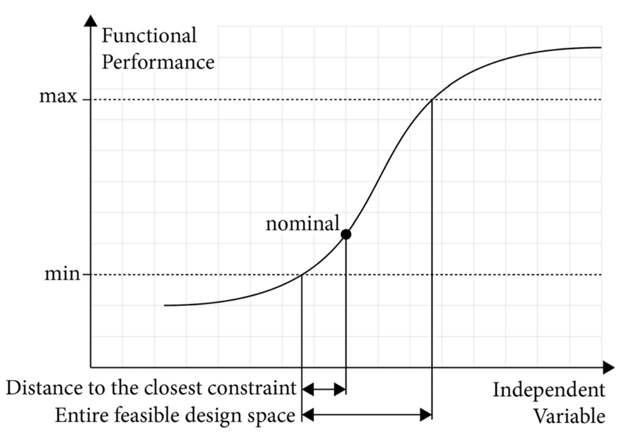


Fig. 3 Size of feasible design space robustness measure (1D)

2) Feasible space:

$$\text{Vol} = |(x|f(x) = f_{\max}) - (x|f(x) = f_{\min})| \tag{8}$$

Figure 3 visualizes the difference between the two concepts of robustness measures in this class. On the one hand, the distance from the nominal to the closest constraint, and on the other hand, the total feasible design space is shown.

In the 1D case with the independent variable being a DP, this metric can directly be compared to the associated production capabilities to determine the expected yield. Interactions and additive effects are not considered. The metrics can be used to compare the influences of independent variables on the function.

For the example of the Toyota gas pedal and its return moment, the size of the feasible design space of the dimension d neglecting interaction and additive effects is

$$\begin{aligned} r_{R_d} &= \min(|(d|f(d) = f_{\max}) - x_{\text{nominal}}|; |(d|f(d) = f_{\min}) - x_{\text{nominal}}|) \\ &= \min(|8.55\,\text{mm} - 6\,\text{mm}|; |4.375\,\text{mm} - 6\,\text{mm}|) = 1.625\,\text{mm} \end{aligned} \tag{9}$$

$$\begin{aligned} \text{Vol}_d &= |(x|f(x) = f_{\max}) - (x|f(x) = f_{\min})| \\ &= 8.55\,\text{mm} - 4.375\,\text{mm} = 4.175\,\text{mm} \end{aligned} \tag{10}$$

The dimension d is, therefore, allowed to vary by 1.625 mm in the worst case. The total allowed variation is 4.175 mm. The results have a direct influence on the setting of tolerances and the question whether those need to be symmetric.

For the multi-dimensional and multi-functional requirement problem, the robustness radius can be calculated analogously; for example, using the definition of the Euclidean distance

$$r_R = \min\left(\sqrt{\sum_i^n (x_{\text{nominal}_i} - (x_i|f(\boldsymbol{X}) = f_{\text{limit}}))^2}\right) \tag{11}$$

The volume of the feasible space, which Suh calls design range [24], for n independent variables and n functional requirements is a metric that describes the entire solution space that fulfills the constraints imposed onto the design by the functional requirements. This volume can be empty if there is no solution or infinite if one or more independent variables are unbounded. In the latter case, it makes sense to constrain the independent variables to reasonable values. Furthermore, the volume is dependent on the number and selection of DPs. Figure 4 shows an example in the case of 2 DPs and 2 functional requirements.

Frey et al. [30] discuss various methods to compute the volume of this polytope that forms the feasible design space. One of them is a method proposed by Lasserre [31], which evaluates a set of linear inequalities of the form $\boldsymbol{Ax} \leq \boldsymbol{b}$

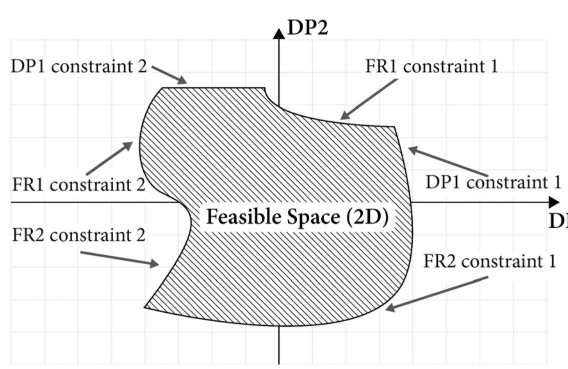


Fig. 4 Example for a feasible design space in 2D

$$\mathrm{Vol}(n, \boldsymbol{A}, \boldsymbol{b}) = \frac{1}{n} \sum_{p=1}^{m} \frac{\boldsymbol{b}_p}{|\boldsymbol{A}_{p,q}|} \cdot \mathrm{Vol}\left(n-1, \tilde{\boldsymbol{A}}, \tilde{\boldsymbol{b}}\right) \tag{12}$$

The calculation is done recursively with $\tilde{\boldsymbol{A}}\boldsymbol{x} \leq \tilde{\boldsymbol{b}}$ representing the system reduced by x_q,where the indices *m, n* are the dimensions of the matrix $\boldsymbol{A}$. Using Lasserre's theorem for the Toyota gas pedal case with the two functional requirements of the return moment and the bending stress yields a feasible space of

$$\mathrm{Vol} \approx 7500 \ \mathrm{Nmm}^6 \tag{13}$$

This volume of the feasible space is independent of the nominal configuration of the DPs which means that it cannot be used for parameter design optimization. However, the metric can be used to determine the influence of a constraint and to compare designs with a similar composition of influencing DPs. Further, the value can be normalized with the system range to make it comparable between designs or to calculate the likelihood of fulfilling the requirements under the assumption of uniform distribution of the DPs [30].

The metrics based upon allowed variation give the possibilities to analyze not only the robustness of a function toward a single and sets of independent variables but also the robustness of a product or system consisting of multiple functions that need to be fulfilled simultaneously. The information about couplings is implicitly included in the formulation of the constraints imposed by the functional requirements.

Summary:

Necessary information entities			Level of complexity (# of functions/# of independent variables)		
Model/ experiment	Functional limits	Expected/ measured variation	1 / 1	1 / n	n / n
✓	✓	–	✓	✓	✓

4.4 Functional Expectancy and Dispersion Robustness Metrics. The robustness metrics of this class are based on the evaluation of the two statistical moment measures expectancy and dispersion (variance) to describe the robustness of a function. For example, robust design pioneer Taguchi proposed the Signal-to-Noise ratio as robustness metric which builds upon the related ideas of quality loss and the mean square deviation [1,2,12], which again refer to the expectancy and variance of the functional performance. As opposed to metrics based on the *size of the feasible design space* as described in 4.2, these metrics do not require information about the functional requirements (limits).

To evaluate the expected functional performance, variance, and associated robustness metrics in this category, a model or experiment and probabilistic information (in the form of probability density functions) of the stochastic variation of the independent variables (DP and noise factors) are necessary (information entities (1) and (3)). However, "calculating these measures [functional expectancy and variance] analytically is almost always impossible" [8]. An alternative way is, therefore, to use approximations usually using Taylor expansion [32]. In the case that measurement data are available for the performance of a function or can be generated by an experiment or an adequate surrogate model, the expectancy and dispersion measures can be calculated from the data samples. The ingoing variation can either be natural (known or unknown from the observed process) or estimated. The mean, variance, and standard deviation can be calculated as follows (Eqs. (14)–(16), respectively):

$$\mu(y) = \int f(\boldsymbol{X}) \cdot p(\mathbf{X}) d\mathbf{X} \tag{14}$$

$$V(y) = \int (f(\boldsymbol{X}) - E(y))^2 \cdot p(\mathbf{X}) d\mathbf{X} \tag{15}$$

$$\sigma = \sqrt{V} = \sqrt{\int (f(\boldsymbol{X}) - E(y))^2 \cdot p(\mathbf{X}) d\mathbf{X}} \tag{16}$$

In classical robustness optimization algorithms, the mean's distance to the target and the variance of a function are optimized simultaneously, where weighting factors determine the prioritization between these two objectives. If the maximum and minimum variations of the independent variables are known, for example, due to quality control and subsequent scrap, the probabilistic problem becomes a deterministic one and the maximum spread of the function performance can be calculated.

Functional expectancy and dispersion robustness metrics can be evaluated to describe the robustness of a function overall and to variation in single or sets of independent variables (DPs or noise factors). In those cases, the conditional expectancy or variance is calculated.

To illustrate these different levels consider again the case of the Toyota gas pedal case. To determine the influence of the dimension h on the bending stress of the friction shoe, or in other words to determine the robustness of the part integrity toward variation in the dimension h, the conditional variance can be calculated as the variation of the average of the bending stress for constant values of h

$$V_h(E_{\sim h}(\sigma_b | h)) = 0.3(\mathrm{MPa})^2 \tag{17}$$

From the analysis of variance (ANOVA), high-dimensional model representation (HDMR) decomposition follows that the sum of all conditional variances—of the main effects plus all existing interactions effects—gives the total variance of the function [9]

$$V(y) = \sum_{\mathrm{i}=1}^{n} V_i + \sum_{\mathrm{i}=1}^{n-1} \sum_{\mathrm{j}=\mathrm{i}+1}^{n} V_{ij} + \cdots + V_{12\ldots n} \tag{18}$$

$$V(\sigma_b) = 31.1 \ (\mathrm{MPa})^2 \tag{19}$$

$$V(M_{\mathrm{return}}) = 98434 \ (\mathrm{N\,mm})^2 \tag{20}$$

The value of robustness metrics that are based on the expectancy measure indicates if a functional performance is on target and can be used to calculate the bias. The variance on the other hand—as calculated in Eqs. (19) and (20) for the bending stress and the return moment, respectively—is difficult to put into perspective without knowledge about the functional requirements and their quality loss away from the target. However, valid comparisons of the robustness of two concepts or for different sets of variations in the independent variables are possible.

Summary:

Necessary information entities			Level of complexity (# of functions/# of independent variables)		
Model/ experiment	Functional limits	Expected/measured variation	1/1	1/n	n/n
✓	—	✓	✓	✓	✓

4.5 Probability of Functional Compliance Robustness Metrics. Robustness metrics belonging to this class evaluate the probability that one or more functions fulfill their requirements under stochastic variation in the independent variables. For the assessment of the probabilities, detailed knowledge about the dependencies between independent variables and functions as well as information about the functional limits (LSL and USL) and the variation of the independent variables in the form of probability density functions is necessary (information entities (1), (2), and (3), respectively).

Under the assumption that the functional output is normally distributed, the probability of functional compliance (or yield rate in a production setting) can directly be calculated from the mean and variance. With knowledge about conditional variances, it is possible to derive the probability of compliance of a function j depending on the variation in single or sets of independent variables (Eqs. (21) and (22)). Further, in the case that the coupling between functions is known, the conditional probabilities can be derived to calculate the joint probability, i.e., the likelihood of functions being satisfactory fulfilled simultaneously (Eq. (23)). In that way, the robustness of multifunctional systems can be evaluated

$$\mathrm{P}_{ij} = \Pr[\mathrm{LSL}_j \leq f_j(x_i) \leq \mathrm{USL}_j] \tag{21}$$

$$\mathrm{P}_{j} = \Pr[\mathrm{LSL}_j \leq f_j(\mathbf{X}) \leq \mathrm{USL}_j] \tag{22}$$

$$\mathrm{P} = \Pr[\mathrm{LSL}_j \leq f_j(\mathbf{X}) \leq \mathrm{USL}_j | \mathrm{LSL}_{k\neq j} \leq f_{k\neq j}(\mathbf{X}) \leq \mathrm{USL}_{k\neq j} | \ldots] \tag{23}$$

Taking the Toyota gas pedal with described dimensions and stochastic variations, the following probabilities and conditional probabilities can be calculated as examples to describe their implications and differences:

$$\Pr[\sigma_b \leq \sigma_{\mathrm{max}_{\mathrm{nom}}}] = 0.99 \tag{24}$$

$$\Pr[\sigma_b \leq \sigma_{\mathrm{max}}] = 0.94 \tag{25}$$

$$\Pr[0 \leq M_{\mathrm{return}} \leq M_{\mathrm{return}_{\mathrm{max}}}] = 0.71 \tag{26}$$

$$\Pr[0 \leq M_{\mathrm{return}} \leq M_{\mathrm{return}_{\mathrm{max}}} | \sigma_b \leq \sigma_{\mathrm{max}}] = 0.68 \tag{27}$$

The probabilities in Eqs. (24) and (25) describe the likelihood of the bending stress being below σ_{max} as functional requirement neglecting and considering the variation in the yield stress, respectively. The difference of 5% relates to the increase in probability of functional compliance, if the yield stress was not subject to variation. Equation (26) describes the likelihood that the return moment is within the limits. Both, the probability of functional compliance for the bending stress and the return moment, were evaluated independently without taking the coupling between them into consideration. The last probability (Eq. (27)) is the conditional probability that both requirements are fulfilled simultaneously, which is lower than the independent probabilities. This demonstrates the error for the assumption of functional independence.

Summary:

Necessary information entities			Level of complexity (# of functions/# of independent variables)		
Model/ experiment	Functional limits	Expected/measured variation	1/1	1/n	n/n
✓	✓	✓	✓	✓	✓

5 Discussion

This section reflects on the verification and validation of the classification scheme offered. This is followed by a summary of the classes of robustness metrics in terms of their implications for defining robustness.

5.1 Verification and Validation of Classification Scheme. By assessing the different robustness metrics by their meaning in the TFM, it was possible to place them into the four classes without ambiguity. The fact that the classes were mutually exclusive meaning that no metrics fit in more than one class is a sign of the strength of the classification scheme and can be considered as a form of verification [33]. The classification scheme was also deemed verified in terms of its "completeness," in the sense that all metrics were able to be classified into one of the four classes. The fact that the classification scheme was derived from the TFM enables the metrics to be easily interpreted during the robust design process, thus ensuring the applicability of the scheme.

In extension to this theoretical verification, the validity of the classification scheme was furthermore evaluated based on the example of the Toyota gas pedal. Its robustness could be easily and clearly quantified using metrics from each of the four classes. It was found that the individual classes represent different interpretations and facets of robustness which have different fields of application within robust design.

5.2 Facets of Robustness. The analysis of the different robustness metrics mentioned in literature revealed the four classes: sensitivity, size of the feasible design space, functional expectancy and dispersion, and Probability of functional compliance robustness metrics.

Sensitivity robustness metrics address the general *robustness of a concept* independent of the specified functional requirements and expected variation. The metrics measure the general capability of a design to dampen or amplify variation. This view on robustness is favorable in earlier design stages when requirements as well as mission profiles and means of production are still unfixed and flexible. Especially, in the concept selection phase, quantified knowledge about the inherent robustness of the different design solutions is of high value.

Metrics from the class of *size of feasible design space* include information about the final requirements which the functions are evaluated against. They quantify the design feasibility taking all functional requirements into consideration and measure, therefore, the *robustness of a design* itself, independent of the variation it is exposed to.

Robustness metrics using *functional expectancy and dispersion measures,* on the other hand, address the spread of the performance of functions resulting from variation in the influencing factors and, therefore, the *robustness of a function.*

Finally, robustness metrics using the *probability* of fulfilling the functional requirements under the influence of variation measure the *robustness of the product* itself and reflect the sum of the sensitivity, requirements, and ingoing variation.

6 Concluding Remarks and Outlook

In this contribution, we systematically reviewed the literature to extract all the different metrics to describe robustness in connection with product development and engineering design. 38 unique metrics were identified and their mathematical descriptions analyzed with respect to their required information and level of addressed complexity. The analysis revealed four distinct meanings of robustness metrics which describe four different facets of quantifying robustness:

1. sensitivity robustness metrics → robustness of a concept
2. size of the feasible design space robustness metrics → robustness of a design
3. functional expectancy and dispersion robustness metrics → robustness of a function
4. probability of functional compliance robustness metrics → robustness of a product

The authors believe that this categorization removes the ambiguity of the term "robustness" ensuring an unambiguous communication allowing the formal introduction of robustness requirements to specification documents and design targets.

Another important contribution of this research is the list of metrics and how they are calculated which gives a comprehensive overview for scholars and practitioners of how robustness can be quantified. The choice of adequate metrics is especially important for simulation-based and computer-aided design and design optimization to ensure viable solutions. Also, the derivation of new metrics can be guided and driven by the classification of metrics and the differentiation of facets of quantifying robustness presented in this paper.

Further research is necessary to close the gap between these objective, quantifiable metrics to proxies (or leading indicators) that are based on good design practice [34,35], such as the variation risk priority number [36,37], the number of over-constraints [3,38] as well as the contradiction index [39]. These proxies play a particularly important role in early design phases where there are no mathematical descriptions of the functions available. The development of further proxies based on objective robustness metrics, as described in this article, would be of high value for engineering designers for the quick estimation of robustness without the need of high-fidelity models.

Acknowledgment

The authors would like to thank Novo Nordisk for their insights and financial support of the DTU-NN robust design program.

Nomenclature

A_0 = maximum loss at variation Δ_0
ANOVA = analysis of variance
D = diagonal matrix
DP = design parameter
E = expected value
f = function
FR = functional requirement
HDMR = high-dimensional model representation
J = Jacobian matrix
LRL = lower requirement limit
LSL = lower specification limit
LTB = larger-the-better requirement
m = functional target
NF = noise factor
NTB = nominal-the-best requirement
$p(.)$ = probability density function
Pr = probability
STB = smaller-the-better requirement
TFM = transfer function model
URL = upper requirement limit
USL = upper specification limit
V = variation
Vol = volume of n-dimensional polyhedron
w = weighting factor
x_i = ith independent variable
X = vector of i independent variables
y = functional output, dependent variable
λ = eigenvalue
μ = mean
σ = standard deviation
σ_a = adjusted standard deviation
Δ_i = perturbation
Σ = covariance matrix

Appendix

Table 5 List of robustness metrics

			Necessary information entities			Level of complexity			
#	Name	Mathematical expression	Model/ experiment	Functional limits	Expected/ measured variation	Independent variables (single/multiple)	Dependent variables (single/multiple)	Robustness metric class	Reference
1	NRS relative to perturbation	$\mathrm{NRS}_i = \frac{\frac{f(x_1,\ldots,x_i\cdot(1+\Delta_i),\ldots,x_n)}{f(X)} - 1}{\Delta_i}$	✓	—	—	single	single	Sensitivity	[10]
2	NRS absolute	$\mathrm{NRS}_i = \left(\frac{f(x_1,\ldots,x_i\Delta(1+\Delta_i),\ldots,x_n)}{f(X)} - 1\right)\cdot 100\%$	✓	—	—	single	single	Sensitivity	[10]
3	Elementary effects/ nominal influence	$\mathrm{EE}_i^{\mathrm{abs}} = \frac{1}{r}\sum_{j=1}^{r}\lvert\mathrm{EE}_i^j\rvert$ with $\lvert\mathrm{EE}_i^j\rvert = \frac{f(x_1,\ldots,x_i\cdot(1+\Delta_j),\ldots,x_n) - f(X)}{x_i\cdot\Delta_j}$	✓	—	—	single	single	Sensitivity	[9,40]
4	Partial derivative	$S_i = \frac{\partial f}{\partial x_i}(X)$	✓	—	—	single	single	Sensitivity	[9,13,20,41]

Table 5. *Continued*

#	Name	Mathematical expression	Necessary information entities: Model/experiment	Functional limits	Expected/measured variation	Level of complexity: Independent variables (single/multiple)	Dependent variables (single/multiple)	Robustness metric class	Reference
5	Normalized partial derivative/sensitivity coefficient	$S_{i\ \text{mean}} = \frac{\partial f}{\partial x_i}(X) \cdot \frac{x_i}{f(X)}$	✓	—	—	single	single	Sensitivity	[10,20,40]
		$S_{i\ \text{Std}} = \frac{\partial f}{\partial x_i}(X) \cdot \frac{\sigma(x_i)}{\sigma(f)}$	✓	—	(✓)	single	single	Sensitivity	[10,13,40]
6	Importance factor	$I_i = \frac{\left(\frac{\partial f}{\partial x_i}(X)\right)^2}{\sum_{j=1}^{N}\left(\frac{\partial f}{\partial x_j}(X)\right)^2}$	✓	—	—	single	single	Sensitivity	[42]
7	FAST Index	$S_{\omega \text{l}}^{(i)} = \frac{\sum_p \left(\lvert A_{\text{p}\omega\text{l}}^{(i)}\rvert^2 + \lvert B_{\text{p}\omega\text{l}}^{(i)}\rvert^2\right)}{\sum_j \left(\lvert A_j^{(i)}\rvert^2 + \lvert B_j^{(i)}\rvert^2\right)}$	✓	—	—	multiple	single	Sensitivity	[9,43,44]
8	Regression coefficients	$\beta_i = \frac{\sum_j \left[\left(\left(x_{i_j} - \mu_{x_i}\right) \cdot \left(y - \mu_y\right)\right)\right]^2}{\sum_j \left(x_{i_j} - \mu_{x_i}\right)^2}$	✓	—	(✓)	single/ (multiple)	single	Sensitivity	[13,19,32]
9	Standardized regression coefficients	$\text{SRC}(y, x_i) = \beta_i \frac{\sigma_{x_i}}{\sigma_y}$	✓	—	(✓)	single	single	Sensitivity	[45]
10	Spearman robustness index	$\text{SRI} = \min\left\lvert \frac{1}{\rho_{x_i} \cdot \beta_{x_i} \cdot \mu_{x_i}} \right\rvert$	✓	—	(✓)	single	single	Sensitivity	[19,46]
11	Spearman robustness index 2	$\text{SRI} = \frac{1}{\sigma_\rho \sigma_{\beta_{x_i} \cdot \mu_{x_i}}}$	✓	—	(✓)	single	single	Sensitivity	[46]
12	Robustness index	$\eta = \frac{1}{N}\sum_{i=1}^{N} \frac{f\left(x_1, \ldots, x_i \cdot (1+\Delta), \ldots, x_n\right) - f(X)}{f(X)}$	✓	—	—	single	single	Sensitivity	[47]
13	Euclidean norm of Jacobian	$\lVert J \rVert_2 = \sqrt{\lambda_{\max}(A^T A)}$	✓	—	—	multiple	single	Sensitivity	[48,49]
14	Frobenius norm of Jacobian	$\lVert J \rVert_F = \left(\sum_{i,j} \lvert a_{ij}\rvert^2\right)^{\frac{1}{2}}$	✓	—	—	multiple	single	Sensitivity	[48]
15	Condition number	$\kappa = \lVert J \rVert_2 \, \lVert J^{-1} \rVert_2$	✓	—	—	multiple	single	Sensitivity	[48–50]
16	Objective robustness index	$\max_{\Delta p} R(\Delta p) = \left[\sum_{i=1}^{n} \left\lvert \frac{f_i(X_0 + \Delta) - f_i(X)}{\Delta f_{i,\text{limit}}} \right\rvert\right]^{\frac{1}{2}}$	✓	—	—	single	single	Sensitivity	[51]
17	Euclidean distance (robustness radius)	$r_E = \min_{X_j : (f_{ij}(X_j) = f_{\max}) \vee (f_{ij}(X_j) = f_{\min})} \sqrt{(X_j - X_{\text{nom}}) D^{-1} (X_j - X_{\text{nom}})^T}$	✓	✓	—	multiple	multiple	Feasible design space	[52,53,54]

Table 5. *Continued*

#	Name	Mathematical expression	Necessary information entities: Model/experiment	Necessary information entities: Functional limits	Necessary information entities: Expected/measured variation	Level of complexity: Independent variables (single/multiple)	Level of complexity: Dependent variables (single/multiple)	Robustness metric class	Reference
18	Mahalanobis distance	$r_M = \min_{X_j:(f_{ij}(X_j)=f_{\max})\ \vee\ (f_{ij}(X_j)=f_{\min})} \sqrt{(X_j - X_{\mathrm{nom}})\Sigma^{-1}(X_j - X_{\mathrm{nom}})^T}$	✓	✓	—	multiple	multiple	Feasible design space	[29,52,55]
19	Feasible volume	$\mathrm{Vol}(n,A,b) = \frac{1}{n}\sum_{p=1}^{m}\frac{b_p}{\lvert A_{p,q}\rvert}\cdot \mathrm{Vol}(n-1,\tilde{A},\tilde{b})$	✓	✓	—	multiple	multiple	Feasible design space	[30,53,56]
20	Min–max interval	$\mathrm{MMI} = f_{\max} - f_{\min}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[8,57]
21	Sensitivity index (2)	$\mathrm{SI} = \frac{f_{\max}-f_{\min}}{f_{\max}}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[32]
22	Percentile difference	$\Delta y_{5\%}^{95\%} = y^{95\%} - y^{5\%}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[58]
23	Variance	$V(y) = \int (f(X) - E(y))^2 \cdot p(X)dX$ $V(y) = \sum_{i=1}^{n}\left(\frac{\partial f}{\partial x_i}\right)^2 V(X_i),$ for independent X_i $V(y) = \sum_{i=1}^{n} V_i + \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} V_{ij} + \cdots + V_{12\ldots n}$ (variance decomposition (HDMR))	✓	—	✓	multiple	single	Functional expectancy and dispersion	[8,9,13,19,59]
24	Standard deviation	$\sigma = \sqrt{V} = \sqrt{\int (f(X) - E(y))^2 \cdot p(X)dX}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[9]
25	Conditional variance	$V_{i1\ldots is} = V_{X_{i1\ldots is}}(E_{X_{\sim i1\ldots is}}(y\lvert X_{i1\ldots is}))$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[9,43,44]
26	Sensitivity index/Sobol index	$S_{i1\ldots is} = \frac{V_{i1\ldots is}}{V}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[9,43]
27	Uncertainty importance	$I_i = \sqrt{V(y) - E[V(y\lvert x_i)]}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[9]
28	Design preference index	$\mathrm{DPI} = E[P(y)] = \int_{y-\Delta y}^{y+\Delta y} P(y)f(y)dy$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[60]

Table 5. ***Continued***

			Necessary information entities			Level of complexity			
#	Name	Mathematical expression	Model/ experiment	Functional limits	Expected/ measured variation	Independent variables (single/multiple)	Dependent variables (single/multiple)	Robustness metric class	Reference
29	Function robustness	$f^R = \frac{1}{N}\sum_{i=1}^{N}\frac{\sigma_f}{\sigma_{x_i}}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[61]
30	Importance index	$\mathrm{II}_i = \frac{\sigma_{x_i}^2}{\sigma_y^2}$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[32,62]
31	Expectancy measure	$F(x) = \int f(X).p(\mathrm{X})dX$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[8,63]
32	Quality loss function	$L(y)_{\mathrm{NTB}} = \frac{A_0}{\Delta_0^2}(y-m)^2$ $L(y)_{\mathrm{STB}} = \frac{A_0}{\Delta_0^2}(y)^2$ $L(y)_{\mathrm{LTB}} = A_0\Delta_0^2\left(\frac{1}{y}\right)^2$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[1,2,12]
33	Mean square deviation	$\mathrm{MSD}_{\mathrm{NTB}} = \sigma_a^2 + (\mu - m)^2$ $\mathrm{MSD}_{\mathrm{STB}} = \sigma_a^2 + \mu^2$ $\mathrm{MSD}_{\mathrm{LTB}} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{y_i}\right)^2$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[1,2,12]
34	Signal-to-noise ratio	$\mathrm{SNR}_{\mathrm{NTB}} = 10\log_{10}\frac{\mu^2}{\sigma^2}$ $\mathrm{SNR}_{\mathrm{STB}} = -10\log_{10}(\sigma^2 + \mu^2)$ $\mathrm{SNR}_{\mathrm{LTB}} = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{y_i}\right)^2\right]$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[1,2,12]
35	Weighted sum robustness	$R_w = w_1 \cdot \lvert\mu_y - m\rvert + w_2 \cdot \sigma_y$	✓	—	✓	multiple	single	Functional expectancy and dispersion	[64]
36	Probabilistic robustness threshold	$\Pr[\mathrm{LSL}_i < f_i < \mathrm{USL}_i]$	✓	✓	✓	multiple	multiple	Probability of functional compliance	[8,58]
37	Design capability indices/error margin index	$C_{dl} = \frac{\mu - \mathrm{LRL}}{3\sigma};\quad C_{du} = \frac{\mathrm{URL} - \mu}{3\sigma};$ $C_{dk} = \mathrm{EMI} = \min\{C_{dl}, C_{du}\}$	✓	✓	✓	multiple	single	Probability of functional compliance	[65,66]
38	Information content	$I = \log\left(\frac{1}{p}\right)$	✓	✓	✓	multiple	multiple	Probability of functional compliance	[24]

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THE CONTRADICTION INDEX (CI): A NEW METRIC COMBINING SYSTEM COMPLEXITY AND ROBUSTNESS FOR EARLY DESIGN STAGES

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ABSTRACT

For complex and integrated products, companies experience difficulties in achieving a satisfactory and consistent functional performance. When a design has "contradicting" parameter/property requirements it often requires fine tuning with numerous design iterations and complex optimizations to find the "sweet spot" where all functional requirements are fulfilled. This often leads to a lack of robustness, where tight tolerances are required and small defects have knock-on effects throughout the product. In this article we propose the Contradiction Index (CI) to gauge how contradicting the requirements of the different parts are with respect to the different functions. This article provides a step-by-step guide for how to estimate the CI for a design. The method is applied to a case study - the FlexTouch®, a Novo Nordisk insulin injection device. When analyzing the CI for each part, against the number of part design iterations, a positive correlation was found. Furthermore, when correlating the CI against the number of challenging tolerances statistical significance was found (p=0.01). It is envisaged that the CI will be a powerful approach to estimate and compare development difficulty and to guide development and design improvements.

INTRODUCTION

The inherent nature of competitive markets drives a trend towards increased functionality with every new product generation. Particularly in hardware and mechanical devices, this implies a higher complexity and level of integration within the product. At the same time, a high and consistent quality and performance throughout the life cycle is of high importance. Performance refers in this context to meeting the functional requirements on a satisfactory level. Secondly, having also a consistent performance despite of any variations determines the success of the product. Ebro et al. [1] classified variations (also sometimes called noise factors) in 5 principle categories being manufacturing, assembly, ambient conditions, load and time dependent variations. Robust design methodology (RDM) is a well acknowledged way of taking these variations into account. Design engineers of the developing companies are consequently challenged to find a design that fulfils all functional requirements but is also robust to variation. However, in particular in the case of complex and highly integrated products, design teams experience difficulties finding the "sweet spot" where all functional requirements are satisfactory met and functional robustness is ensured. Gribble states that "small changes to a complex coupled system can result in large unexpected changes in behavior, possibly taking the system outside of its designers' expected operating regime" [2]. Compromises and trade-offs in numerous design iterations as well as increased costs for manufacturing and quality control is the result. The implications of the complexity and the level of integration on the performance and the robustness consequently need to be well understood. Whereas, in practice, increased efforts are experienced first and foremost in detailed design stages, e.g. computer simulations and excessive test campaigns to verify and optimize the design, the relevance of the conceptual design phase is frequently neglected. While optimization techniques can greatly improve a design during the detailing phases, it is the design concept that places constrains and ultimately limits the achievable performance and robustness of a product [3, 4]. "A poor concept can rarely be manipulated to achieve commercial success" [5]. It is therefore desired to evaluate the complexity and robustness of a given concept in the beginning of the design process to make the right decisions and to identify potential risks in development and robustness to save development time and cost.

State of the art

There are various methods to describe and evaluate the complexity and/or robustness of concepts and designs. El Maraghy et al. [6] name complexity theory, entropy or information theory as the basis for common complexity metrics. The Design Structure Matrices (DSMs) and the House of Quality (HoQ) in Quality Function Deployment (QFD) [7] are two of the most common tools for the development of complex systems. Eppinger and Browning [8] describe various examples related to complex system development addressing problems like modularity, outsourcing, system integration, etc. DSMs are subject to many research projects and have been developed further and augmented to improve the visualization, optimization and analysis. In QFD the House of Quality is another matrix approach that supports product development [9]. Customer requirements are mapped against engineering characteristics. In the 'roof of the house' engineering characteristics are compared against each other to find contradictions. Based on DSM and HoQ Mocko et al. [10] derived a modelling scheme to map and analyze relationships between requirements, functions, components and engineering characteristics. Shafiei-Monfared et al. [11] use graph theory and DSMs to measure the complexity of development projects. The metric is based on estimated man-hours per project with respect to technical and managerial aspects. However, the method needs experiences from previous similar projects and knowledge about required skills of the engineers.

Robustness considerations in the conceptual design phase are rather uncommon. That holds for single functions and on systems level. Robust Design tools to evaluate the concept robustness are rare. Robust concept exploration techniques have been proposed to screen the design space for a robust concept [12-14]. Other recent contributions in the field of robust design focus on robust design optimization [15-17] addressing designs in later stages of the development. However, there are design rules conveying robustness such as Suh's Axiomatic Design [18]. Uncoupling of functions and the reduction of the information content for the concept enhance the robustness of the final product. The information content is also a measure of the complexity of the design comparing the design range with the common range. Kinematic Design and Design Clarity aim at the definition of the right set of constraints imposing more robustness due to more predictable interfaces of the individual parts [1]. However, in the case of Kinematic Design only the right mobility is ensured. Design Clarity is only applicable for more mature designs since the interfaces are assessed on a detailed level. Moreover, only few contributions address the complexity in the context of robustness. Grussenmeyer et al. present a framework for the influence of complexity and robustness on production performance [19]. De Biagi et al. propose a measure for quantifying the complexity and robustness of a frame structure based on graph theory [20].

Overall, in particular for designs that cannot be designed exclusively under robustness considerations a new approach is needed. The lack of methods evaluating the complexity and robustness in early design stages leads to the question of how a concept can be evaluated in terms of minimal risk for poor performance and robustness in the case of a complex and highly integrated product, where many functions are dependent on the same parts and design parameters.

Objective and Scope

In this paper we propose a methodology to analyze a concept's complexity and design parameters. The technique is based on an evaluation of whether the functional requirements (FRs) imposed on organs and parts are in conflict. The level of conflict or 'contradiction index' is used as an indicator for potential compromises and trade-offs later in the detailed design stage that will penalize the performance and robustness of the final product. This approach augments common methods like DSM and QFD. We applied and validated the proposed approach in development projects for prefilled insulin injection devices at Novo Nordisk. For this article the FlexTouch® insulin pen has been used as an example. It combines a high level of functional integration with demanding requirements and a high volume production with an automated assembly line. High and consistent performance, reliability and robustness are of crucial importance to maintain compliance to FDA standards and control costs due to scrap, quality control and redesign efforts.

The goal is to support the concept selection for complex and integrated products by helping to foresee potential issues and risks related to functional performance and robustness in later development stages. Furthermore, the output of the method suggests areas of potential design improvements and can be used for task prioritization and design optimization.

PROPOSAL OF A NEW APPROACH

In the following we will describe the rational and application of the new method.

Rational

From the Axiomatic Design framework [18] follows that an uncoupled design yields better robustness opportunities (Independence Axiom). Also, the fewer (coupled) design parameters (DPs) a function has the more robust it is (Information Axiom). However, in many cases these axioms cannot be obeyed due to restrictions of other kinds (business case, platform architecture, other DfX areas). The results are complex and integrated products. It is understood that uncoupled designs are easier to optimize and to find the "sweet spot" that fulfills all functional requirements. Further, robust concepts yield more possibilities of achieving a robust product.

Figure 1 shows the transfer functions of two functional requirements FR1 and FR2 that are coupled through a design parameter (DP). The requirements are of the kind "nominal-is-best". For the ease of the diagram the FRs are scaled such that their required nominal and upper and lower limits match. As can be seen from the diagram, there is a range of the design parameter that fulfills both FRs in a satisfactory manner. However, the acceptable variation of the design parameter to fulfill both FRs at the same time is smaller than the acceptable variation for the single FRs.

$$Robustness\ of\ coupled\ FRs \leq Robustness\ of\ single\ FRs$$

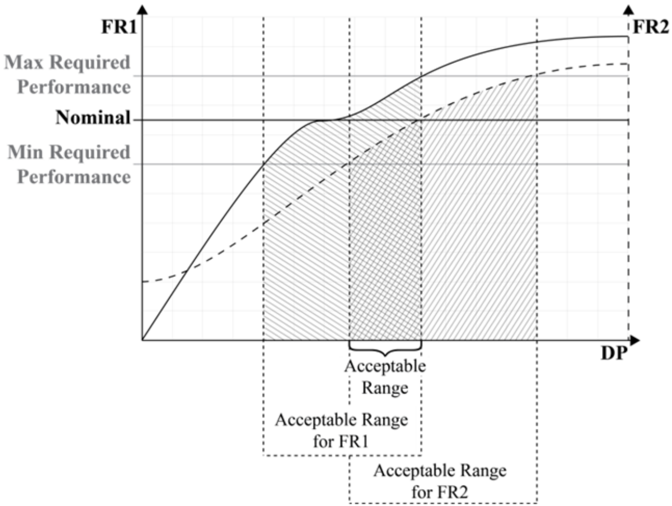

Figure 1: Coupled functional requirements of the kind "nominal-is-best"

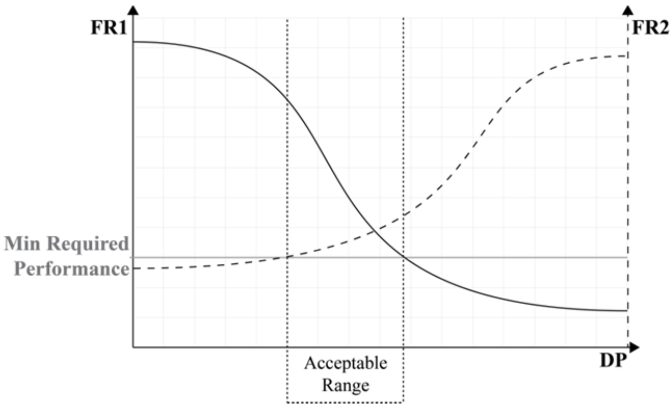

Figure 2: Negatively coupled functional requirements of the kind "max-is-best"

In a real design situation this results in tight tolerances and small margins and safety factors bearing the risk of non-conformance and robustness issues. There are two other kinds of couplings for functional requirements of the kind “max/min-is-best”. Figure 2 shows the transfer functions of two negatively coupled functional requirements. Negatively coupled means the two functions have contradicting requirements towards a DP. As can be seen on the graph, the acceptable range of values for the DP can potentially be small and sensitive. In the case of two functions being positively coupled the performance of both functions tend in the same direction for the shared DP (see Figure 3). That means for example that for higher values of the DP the performance of both functions increase or decrease. The feasible range of the DP is likely to be bigger than for the negative coupling yielding more opportunities to improve the robustness.

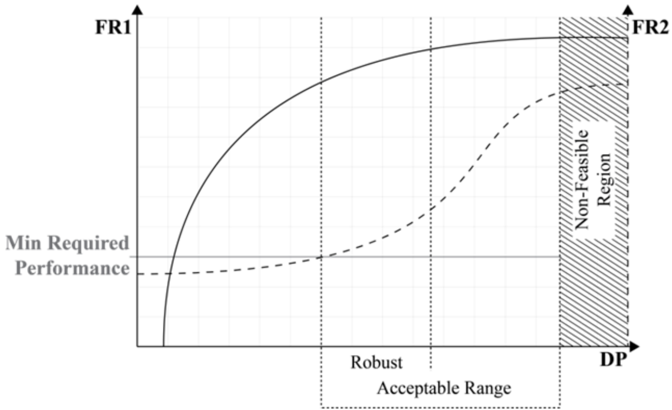

Figure 3: Positively coupled functional requirements of the kind "max-is-best"

It can be concluded that firstly, coupled FRs bear a higher risk of being non-optimal due to compromises and trade-offs and of being less robust. This matches with axiom 1 of AD. Secondly, there are two different kinds of couplings for max/min-is-best requirements which are negative and positive couplings. In these cases a positive coupling is the preferred one yielding more opportunities for increasing the performance and the robustness.

In the actual design context the DPs that couple functions are properties and measures of the parts that are comprised by the organs that address the functions. The rational for the method proposed below is to find the coupling parts for a design concept and evaluate the requirements that are imposed on them. Based on the discussion above, the assumption is that fewer contradicting requirements on the single parts reduce the risk of a compromised functional performance and a higher robustness of the final product. Further, following the Information Axiom of AD the number of DPs influencing a function affects the robustness and will also be addressed with the proposed method.

Approach

The technique is based on an evaluation of whether the functional requirements (FRs) imposed on organs and parts are in conflict. The proposed method consists of 4 steps: 1) decompose the concept to organs and parts and allocate all FRs to the organs realizing the associated function. 2) Assign desired properties to every individual part that maximize its performance for a certain FR. 3) Estimate the number and nature of design parameters of a part towards a FR. 4) Evaluate the contradiction index on part and FR level. The approach is meant to be applied by the responsible design engineers. The necessary level of information is at least a concept solution including all necessary parts and their (preliminary) planned interactions. Detailed knowledge about interface designs, lengths and tolerances are not necessary. The proposed method is addressing problems in early design with the described level of available information. The evaluation of development risks in terms of achievable and robust performance is of main interest. Non-functional (non-technical) requirements as for example budget or launch date requirements are neglected for this evaluation.

Step 1

As for complexity methods like DSM and QFD (House of Quality) the concept is first decomposed into its organs and subsequently into its parts. Organs are the means which address the physical realization of the functions. For the designing engineers this task should be straight forward. Secondly, the functional requirements are assigned to the associated organs. Generally speaking, the selection of functions under investigation depends very much on the product. We suggest to limit the number of functions to the active functionalities defined by the overall product specification and to exclude passive functions like "provide support"-functionality as defined by Scalice [21]. Following Tjalve [22] the "provide support"-functionality is not considered a part of the functional structure of the part. Table 1 shows exemplarily the system decomposition.

	Functional Requirement	Part 1	Part 2	…
Organ 1	FR 1	x		
	FR 2			
Organ 2	FR 3	x	x	
	FR 4			
⋮	⋮			

Table 1: System decomposition

An organ is defined by the parts and part-interfaces that create a function. The function is the "organ's ability to create an active effect" [23]. The functional requirements are therefore linked only to one organ. The underlying assumption is that a functional requirement stretching over multiple organs can be broken down to sub-functional requirements for the individual organs. Multiple FRs addressed by one organ is possible. Finally, the requirements for each organ should be clearly defined. Obviously, these can change but for the time of the concept assessment they are assumed to be fixed.

It was found practical to include the measure (unit) and sort (max, min, nominal is best) of the functional requirements and to verbally describe influencing phenomena for each of the FRs (e.g. friction, spring characteristics, position, orientation, size etc.). The goal is to be able to map functional dependencies and specify these in step 2.

Step 2

The second step is the main evaluation. The intention is to evaluate the level of contradiction in the functional requirements projected onto the single parts. The conceptual layout and more precise the organs of the product addressing the functional requirements, determine the requirements on the properties and attributes of the single parts. These properties can be material related (e.g. electrical conductivity, hardness, strength, e-module etc.), geometry related (e.g. position, orientation, size etc.) or material and geometry related (e.g. stiffness, weight etc.). These properties and attributes having an influence on the functional performance differ from product to product and can also differ from part to part depending on the nature of the organ (mechanical, electrical, etc.). For the evaluation of the functional requirements, the properties need to be of a kind that can be judged desirable or undesirable from functional point of view. The idea is to cover the most important aspects that can influence the performance of the functions in the final product. This can go as far as a property being necessary or detrimental to achieve the functionality. The important thing here is only the independence of the properties to prevent double accounting of contradictions.

Pimmler and Eppinger [24] introduced a scoring scheme to address and map the influence and importance of interactions in complex products. They used the evaluation of interactions to "define the product architecture and to organize the development teams". They rated product specific interactions on a 5-level scale from required (+2) to detrimental (-2) to quantify the relative importance for the single interactions. Building upon this idea we developed a scoring scheme evaluating certain part properties and characteristics with respect to their importance for a functional requirement. We augmented the scale by a sixth level to account for unknown imposed requirements on the part due to functional requirements of the kind "nominal-is-best". Table 2 shows the six categories required, desired, unknown, indifferent, undesired and detrimental and their explanations.

Required	+2	The property is necessary to fulfil the functional requirement.
Desired	+1	The property is beneficial for the performance of the function.
Unknown	+/-	For nominal is best requirements the influence of a property can be either desired or undesired
Indifferent	0	The property does not affect the performance of the function.
Undesired	-1	The property causes negative effects but does not prevent functionality.
Detrimental	-2	The property must be prevented to achieve functionality.

Table 2: 6-level scoring scheme

The main task in this step is to choose appropriate properties and rate the importance with the scores shown in Table 2. The scoring should be done by the responsible design and development engineers. Every part shall be rated individually towards a specific functional requirement regardless of other requirements or imposed behaviors etc. Part properties affecting functions with requirements in the category nominal-is-best are rated with +/- since the nominal performance and the sensitivities are unknown at this stage. In the case of mechanical designs and geometry dependent properties it was also found to be useful to differentiate between different independent directions. The requirements on stiffness in one direction can for example be independent of those in another direction. For the investigations of a cylindrical insulin pen described in this article, cylinder coordinates (directions z, r, phi) have been used. However, the choice of the coordinate system should be taken depending on the product.

Step 3

To further estimate the contribution of a part towards the robustness of a function, the number of influencing parameters (design parameters) is being assessed. Following the second axiom of Suh's Axiomatic Design, the information content and therefore the probability of success of a function is dependent on the number of design parameters.

The assessment of influencing parameters can be difficult for certain functions. Especially in the early design phase were details have not been worked out yet and only a rough idea of the structure and the interactions between parts exists, only estimations are possible. For incremental designs, derivatives or in companies that have experience and expertise in designing the product type under investigation a more accurate number can be derived. It makes sense to differentiate between different directions what also reflects in most cases the way the part is machined. However, the main purpose is to estimate the number to get an overview as early as possible. Considerations of the kind of functional requirement, interfaces, active surfaces as well as whether a force or torque is being transmitted through the part help to estimate the number of influencing parameters.

Step 4

The fourth step is the derivation of the contradiction index.

Part Level:

To derive the contradiction index on part level, the requirements from the functions on the parts as evaluated in step 3 need to be compared for each of the properties in each of the directions. A contradiction is present if there are two opposing requirements. For the applied scoring scheme (Table 2) this translates to opposing signs of the scores for the properties for a direction. The contradiction score is in that case the difference between the highest and the lowest score. For +/- entries +1 or -1 is chosen to give the highest contradiction score to indicate that in a worst case scenario there might be a contradiction.

For example, if one functional requirement desires (+1) a high stiffness of a part in radial direction which is detrimental (-2) for another function and undesired (-1) for a third function the contradiction score is 3, which is the highest difference between the scores. In the case that a part's property does not matter for a certain function (indifferent, score = 0) or all dependent functions require it to be in the same way (for example +2 for FR1 and +1 for FR2) there is no contradiction and the contradiction score is zero. Table 3 shows some examples for the calculation of the contradiction score. Note that the score is always positive and cannot be higher than 4. Multiple requirements on a property in a direction do not increase the score further.

Part 1				
Property: Stiffness in r- direction				
Example	FR 1	FR 2	FR 3	Contradiction
1	+2	-1	-1	3
2	-2	+2	-1	4
3	+1	-1	+1	2
4	+2	+1	0	0
5	-1	-1	-1	0
6	-1	0	+/-	2

Table 3: Examples

For the number of influencing factors only the highest number of a direction is taken to reflect the fact that surfaces (and therefore also the DPs) can be used for multiple functions.

Once the contradiction scores have been calculated for all functions and directions the part contradiction index (CI) is calculated as the sum of all contradictions and all influencing parameters combining both of Suh's design axioms to a metric.

$$CI_{Part} = \sum_{Directions} \left(\sum_{Properties} (Contradiction) + No.of\ DPs \right)$$

Organ Level:

Analogously it is possible to calculate the contradiction index for every organ by summing up the part CIs contributing to a certain organ.

$$CI_{Organ} = \sum_{Contributing\ Parts} CI_{Part}$$

In that way it is possible to identify organs, i.e. solutions to functional requirements that are at risk of a high level of trade-offs compromising the performance and the robustness. Different solutions and alternatives for addressing a functional requirement can be evaluated.

Functional Requirements Level:

The same technique can be applied to derive the CI for the functional requirements. The CI implicitly considers the impact of the length of tolerance chains by summing up the shared influencing parameters (design parameters).

To identify conflicting couplings of different functional requirements, the imposed requirements on the parts can be evaluated for any two functions. In this instance the contradiction level of the contributing parts is not derived taking all FRs into consideration but only the two under investigation. The CI for the first order coupling of two functional requirements is then:

$$CI_{FR1-FR2} = \sum_{shared\ parts} CI_{Part}(FR1, FR2)$$

A DSM for the functional requirements can be generated giving an overview of first order functional couplings and contradictions. It gives a symmetrical matrix since the coupling is the same from FR1 to FR2 and the other way around. Table 4 shows exemplarily a functional requirements DSM. It is important to remember that the functions are only coupled because their organs share parts. Before designing the organ structure, all functions are uncoupled by definition [25].
Information about the criticality and the actual tolerance of the single FRs can be used to evaluate the risk of having certain couplings. Alternative solutions for decoupled FRs can be derived. Expert knowledge and experiences from previous projects for a similar product can be used to judge if a risk can be taken or not.

	FR1	FR2	FR3	FR4
FR1	x	Conflicts between FR1 and FR2	Conflicts between FR1 and FR3	Conflicts between FR1 and FR4
FR2		x	Conflicts between FR2 and FR3	Conflicts between FR2 and FR4
FR3			x	Conflicts between FR3 and FR4
FR4				x

Table 4: Functional Requirements DSM

A CASE STUDY

The approach presented in this article has been applied to various development projects for prefilled insulin injection devices at Novo Nordisk. The case study for this paper is the FlexTouch® pen. It has an integrated design, where single parts contribute to multiple organs and functions. The requirements on the performance of the pen are strict to comply with FDA standards. With a production volume of multiple million units per year, a robust design is of high importance. For this study, an early stage design iteration of the FlexTouch® has been analyzed with the proposed method to derive the contradiction index of the concept. Figure 4 shows exemplarily a conceptual sketch of the FlexTouch®. The CI is used to challenge the solution and to estimate development difficulties and robustness issues in the transition to the embodiment phase.

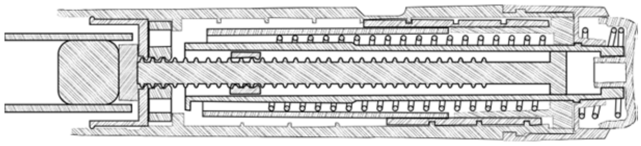

Figure 4: Conceptual sketch of the FlexTouch®

For the first step of the proposed method the concept shall be decomposed into organs, their parts and the functional requirements they address. The pen's engine module in the conceptual stage consists of 8 organs addressing the functional requirements. The organs comprise 14 parts in total including 2 springs from external suppliers. Table 8 (Appendix A) shows a matrix representation of the pen. Detailed information about materials, specific dimensions or tolerances are yet unknown.
For the second step we firstly reviewed the functional requirements to judge the general properties of the parts that influence the final performance of each function. As described earlier, the properties can be divided into three categories: 1) geometry related, 2) material related and 3) geometry + material related. The choice of the properties to be evaluated also depends on the available information and knowledge about the concept. For the example case of the FlexTouch® insulin pen, it has been found that the stiffness and the play of the single components are the most important conceptual properties of the pen with respect to the functional performance. The stiffness was chosen due to requirements on delivering torque and reliable positioning without distortion or bending. Also, stiffness relates to the jamming of mechanisms when geometric variations occur. The play or clearance of parts is important for the positioning requirements but also has an influence on the friction between parts for too tight clearances and interferences. Cylindrical coordinates have been used for the evaluation to distinguish between directions.
The Piston Rod will now be taken as an example to illustrate the contradiction index. The Piston Rod is ultimately driven by the motor module of the pen to translate the rotational input to an axial translation, driving the plunger in the cartridge to deliver the insulin. High demands on the dose accuracy put strict requirements on the position of the Piston Rod, whereas the required delivery torque needs to be maintained even for geometrical variations of the associated parts. From Table 8 (Appendix A) it can be read off that the Piston Rod has an influence on the EOC System and the Linear Actuator organ. We will examine the Actuator organ with its functional requirements on the delivery torque and the dosing accuracy. Table 5 and Table 6 summarize the evaluation of the functional requirements imposed onto the Piston Rod in the three directions. To maximize the delivery torque a high stiffness around phi and play in all three directions to reduce potential problems with friction is desired. The dose accuracy requires a stiff Piston Rod and ideally no play in z- and phi-direction to meet the requirements. The third step of the method addresses the number of influencing parameters which are in the case of the Piston Rod one in each direction due to the thread.

FR 1: Delivery Torque

Direction	z	r	Phi
Stiffness	0	0	1
Play	1	1	1
No of influencing parameter	1	1	1

Table 5: Functional Requirements on the Piston Rod for the Delivery Torque

FR 2: Dosing Accuracy

Direction	z	r	Phi
Stiffness	1		1
Play	-2		-2
No of influencing parameter	1		1

Table 6: Functional Requirements on the Piston Rod for the Dosing Accuracy

In the fourth step the contradiction index is evaluated. The requirements on the properties of the Piston Rod are compared as described earlier in the article.

Contradiction Index (CI)

Direction	z	r	Phi
Stiffness	0	0	0
Play	3	0	3
No of influencing parameter	1	0	1

Table 7: Resulting Contradiction Index for the Piston Rod

Table 7 summarizes the contradictions for the Piston Rod. The total contradiction score is 3 + 3 = 6 (coming only from the contradiction on the play requirements). With the 2 shared influencing parameters it results in a CI of 8 for the Piston Rod. The results increase the awareness of the designer for this coupling of FRs for the Piston Rod. The resulting implications are high demands on tolerances for the thread of the Piston Rod and the mating nut and a compensation of potential friction issues by selecting an appropriate torque spring. Table 9 (Appendix A) shows the resulting functional DSM summarizing the functional couplings and their level of contradictions for the FlexTouch®. It highlights the potential risks of not meeting requirements robustly by showing the CI. Based on the matrix design engineers and the chief engineer can judge risks and plan mitigations.

VALIDATION

To validate the usefulness of the Contradiction Index (CI) and the proposed method, the results for the early concept of the FlexTouch® as described above have been compared against actual development data of the pen. The question to answer is whether the risks suggested by the method reflect the actual development, performance and robustness of the pen. The assumptions are that for parts and functions with a higher CI and coupling more iterations and tighter tolerances are likely to be necessary to fulfil the functional requirements nominally but also robustly. Contradictions imply that compromises and trade-offs are probable, which have an effect on the performance but also on the robustness of a function as discussed in this paper. For this study, change notes and the final drawings of the pen have been reviewed to correlate the number of design iterations as well as the number of demanding (< IT13 for injection moulded parts) and challenging tolerances (< IT12 for injection moulded parts) to the CI of the parts.

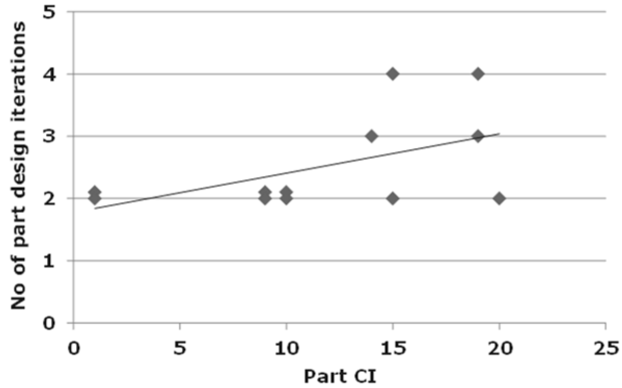

Figure 5: No. of Part Design Iterations vs Part CI

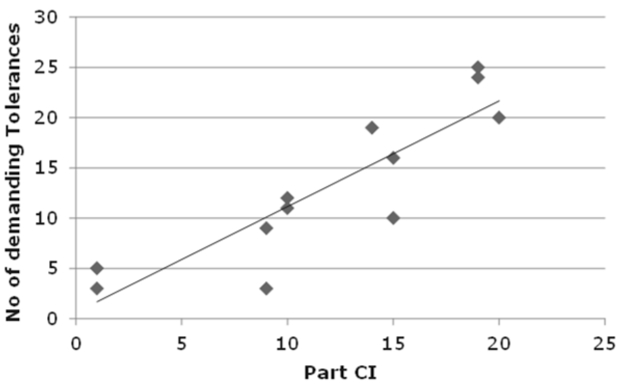

Figure 6: No. of challenging Tolerances vs Part CI

Furthermore, design engineers and the chief engineer were asked for the usefulness and applicability of the method and its output. Figure 5 and Figure 6 show the correlations between the number of part design iterations and challenging tolerances versus the part CI respectively. Note that the 2 springs from external suppliers have been excluded here. From the plot in Figure 5 there seems to be a tendency towards a correlation between the number of part design iterations and the part CI; however, the correlation was not statistically significant in a linear regression model ($p=0.25$). In contrast, we found a statistical significant correlation between the number of challenging tolerances and the part CI ($p=0.01$), which can also be seen in the plot in Figure 6. However, it also has to be mentioned that there is a correlation between the number of functions a part contributes to, to the number of challenging tolerances ($p=0.03$), which is a bias. Nevertheless, the analysis suggests a stronger correlation with the CI. After all the number of data points is quite small, weakening the statistical analysis and can lead to false correlations. The prerequisite for linear modelling of having normally distributed values for the variables can also only be assumed for this few observations. More case studies are necessary to improve the validity of the analysis. Also a more detailed analysis of the change notes and tolerances is required to reduce the mentioned bias. To judge the correlation of the CI to the robustness of the final product, production data like scrap rates and market failures need to be analysed. Generally speaking, the validation is difficult since the development of a product is a complex activity with various influencing factors. Furthermore, the proposed method evaluates the risk for a given concept, which is difficult to validate with only one case study as proposed here. However, the design engineers applying the method to other development projects and the chief engineer gave positive feedbacks for the usability and applicability of the method. The increased awareness of couplings and contradictions helped making design decisions and concept selections.

DISCUSSION

The proposed method addresses the complexity and robustness of concepts by evaluating the level of contradiction of the requirements on the parts. The goal is to estimate the risks for difficulties finding a design solution that fulfils all functional requirements in a robust manner. Especially in the early design phase this is of high value, as experience shows that substantial time is spent in the later design phases tweaking design parameters and squeezing tolerances to compensate for contradicting functional requirements. The concept decides about the performance and robustness of the final product. Potential trade-offs and compromises lower the performance and can lead to sensitive designs. Another effect could also be small margins and safety factors, which further increases the risk of product failures. However, the method has its limitations. The CI does not conclude anything about the general feasibility of the concept and whether there is "sweet spot" that fulfils all FRs. It also does not predict the final functional performance of the product and whether it will be robust in absolute terms. The CI score can slightly differ dependent on the applying engineer. The distinction between required/desired and between undesired/detrimental needs to be well defined. However, the overall message of contradicting requirements will not change. The method and the CI is therefore rather an indicator for couplings and contradictions. It can be used as a relative measure to compare concepts and to increase the designers' understanding of the functional coupling of the design. The information about couplings of the functions and their contradictions in the context of a specific design solution is of high value for the design team. Together with the engineers' experiences, the actual requirements on the single functions and the knowledge about production capabilities the risks on the functions can be evaluated and it can be decided whether certain risks can be accepted or a redesign is necessary. Also, tasks can be prioritized based on the output of the method. Conventional robust design methods for the conceptual design phase are rather design guidelines that can or cannot be applied depending on other constraints which can be of engineering or business nature.

Other methods like DSM and QFD give indications about couplings of functions and designs. Especially DSMs and MDMs are used in various ways and support the designers to cluster, optimize and integrate design solutions [8]. However, the kind of coupling and whether there are inherent contradictions imposed on the design is not shown. The "roof" of the house of quality addresses interactions and conflicts but only on the level of engineering characteristics [9]. The proposed approach is seen as an augmentation to DSMs and QFD to evaluate designs not only from the pure coupling point of view but also give an indication where the problems in the design might be and which parts might have the biggest development risk. In the domain of robust design methods evaluating a concept's robustness like robust concept exploration techniques [10-12] require a meta-model to describe the system which again needs a certain detail of system knowledge. Kinematic Design, Design Clarity [1] or Axiomatic Design [18] give the designer a good guidance of how to design for robust products but might not be applicable due to mentioned reasons. Other robust design methods like robust optimization techniques or sensitivity studies of any kind require a detailed design and are not applicable in the early phases. The presented validation is only an indication of whether the CI is meaningful or not and needs to be backed up and confirmed by further cases also from different kinds of products. However, the application on current development projects and the positive feedback from the engineers using it as well as from the chief engineer give a promising indication about the usefulness of the method. The awareness of couplings and contradictions supports design decisions with a holistic view on the system taking all functional requirements into account.

CONCLUSIONS

In this article we propose a method to evaluate the complexity and the robustness of highly integrated products on concept level by evaluating the concept with respect to contradicting requirements. The approach has proven to be useful and relevant for design engineers in the early design phase to evaluate and compare different concept solutions. The method's output is the Contradiction Index (CI) for parts and functions measuring the level of contradiction of couplings. With this it is possible to judge risks for potential trade-offs in later design stages compromising the performance and the robustness of the design ultimately leading to costly late design changes or tight tolerances and costs on quality control.

The method has been validated with Novo Nordisk's FlexTouch® insulin injection pen. It was found that the CI has a strong correlation to the number part design iterations as well as with the number of challenging tolerances. However, further investigations and case studies also on different kinds of products are necessary to further develop the method and confirm the usefulness. More and better data is necessary to further validate the Contradiction Index. The assessment of scrap data, market failures and other robustness indicators can further confirm the goodness of the risk evaluation of the CI with respect to functional robustness to variations.

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Appendix A: Results for the FlexTouch® case study

#	Organs	Functional Requirement	FR domain (Force, Torque, Pos)	FR type	Influences	Nut	Piston Rod Guide (PRG)	Piston Rod	Piston Washer	EOC Ring	Reset Tube	Housing	Ratchet	Spring Base	Dial	Push Button	Scale Drum	Return Spring	Torque Spring
						Parts													
1	Organ 1	FR 1	P	min error	Pos. + Orient., length of tol chain, accuracy of threads			x		x	x								
2	Organ 2	FR 2	P	min error	Position, orientation, length of tol chain							x	x	x			x		
		FR 3	P	min error	Position, orientation, length of tol chain														
3	Organ 3	FR 4	T	nom	Design of torque transmission teeth						x	x	x		x				
		FR 5	F	max	Stiffness and no. of ratchet arms, dim. of arms, overlap, radii														
4	Organ 4	FR 6	T	max	Stiffness of torque chain					x		x	x		x	x	x		x
		FR 7	T	min	Torque arms, spring characteristics, friction														
5	Organ 5	FR 8	P	max	Axial position		x			x	x	x	x		x	x	x	x	x
		FR 9	F	min	Friction														
6	Actuator organ	Dosing accuracy	P	min error	Pos. + Orient., length of tol chain, accuracy of threads	x	x	x	x		x	x	x				x		
		Delivery torque	T	max	Torque arms, spring characteristics, friction														
7	Organ 7	FR 12	F	max	Stiffness and no. of ratchet arms, dim. of arms, overlap, radii		x					x							
8	Organ 8	FR 13	F	max	Stiffness and no. of ratchet arms, dim. of arms, overlap, radii									x			x		

Table 8: Partly anonymized Decomposition Matrix of the FlexTouch®

		FR 1	FR 2	FR 3	FR 4	FR 5	FR 6	FR 7	FR 8	FR 9	Delivery torque	Dosing accuracy	FR 12	FR 13
Organ 1	FR 1				0 2 / 1			0 8 / 3		0 2 / 1	0 6 / 3	0 0 / 3		
Organ 2	FR 2			0 0 / 4		0 0 / 3	0 0 / 1	8 10 / 5	0 0 / 1	2 2 / 1	8 8 / 4	0 0 / 5	0 0 / 2	0 3 / 1
	FR 3					0 0 / 2	0 0 / 2	0 8 / 4	0 0 / 1	0 2 / 1	3 6 / 4	0 0 / 4	0 0 / 2	0 6 / 2
Organ 3	FR 4							0 8 / 4	0 6 / 3	2 2 / 2				
	FR 5						0 0 / 1	5 12 / 6	0 0 / 2	3 4 / 3	2 6 / 3	0 0 / 3	0 0 / 3	
Organ 4	FR 6							0 0 / 1			3 0 / 1	0 0 / 1	0 0 / 1	0 0 / 1
	FR 7								0 6 / 3	0 0 / 6	0 0 / 6	10 12 / 6	0 6 / 3	0 0 / 1
Organ 5	FR 8									0 0 / 1	0 2 / 3		0 0 / 2	
	FR 9										0 0 / 5	4 6 / 3	0 4 / 3	0 0 / 1
Actuator organ	Delivery torque											14 / 11	5 10 / 6	0 0 / 1
	Dosing accuracy												0 0 / 2	0 3 / 1
Organ 7	FR 12													
Organ 8	FR 13													

Table 9: Partly anonymized Functional Requirement contradiction DSM

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ORIGINAL PAPER

A model-based approach to associate complexity and robustness in engineering systems

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Abstract Ever increasing functionality and complexity of products and systems challenge development companies in achieving high and consistent quality. A model-based approach is used to investigate the relationship between system complexity and system robustness. The measure for complexity is based on the degree of functional coupling and the level of contradiction in the couplings. Whilst Suh's independence axiom states that functional independence (uncoupled designs) produces more robust designs, this study proves this not to be the case for max-/min-is-best requirements, and only to be true in the general sense for nominal-is-best requirements. In specific cases, the independence axiom has exceptions as illustrated with a machining example, showing how a coupled solution is more robust than its uncoupled counterpart. This study also shows with statistical significance, that for max- and min-is-best requirements, the robustness is most affected by the level of contradiction between coupled functional requirements ($p = 1.4\mathrm{e}{-36}$). In practice, the results imply that if the main influencing factors for each function in a system are known in the concept phase, an evaluation of the contradiction level can be used to evaluate concept robustness.

Keywords Robust design · Complexity · Axiomatic design · Coupling · Contradiction

1 Introduction

Many products from hairdryers to systems like a spacecraft become more and more complex and integrated. Functionality is being added with every product generation as technology advances. For example, Figs. 1 and 2 show exemplarily the evolution of car safety features and added technology for every generation of the Apple iPhone, respectively. The performance but also the robustness against variation and noise factors of the functions is of high importance.

The pursuit of robustness, i.e. insensitivity to variation in noise (type I Robust Design) and design parameters (type II Robust Design), challenges the developing companies. "Small changes to a complex coupled system can result in large unexpected changes in behaviour, possibly taking the system outside of its designers' expected operating regime" (Gribble 2001). The analysis of large-scale design/engineering networks points towards the same conclusion that complexity i.e. "design coupling" tends to negatively influence system robustness (Braha and Bar-Yam 2004, 2007). The question arises how large the impact of complexity on robustness is and whether generalizations can be made.

There are various design guidelines available fostering a "good" and robust design. One of them—axiomatic design (AD) by Nam P. Suh (2001)—addresses the complexity and coupling of the design. The first axiom promotes

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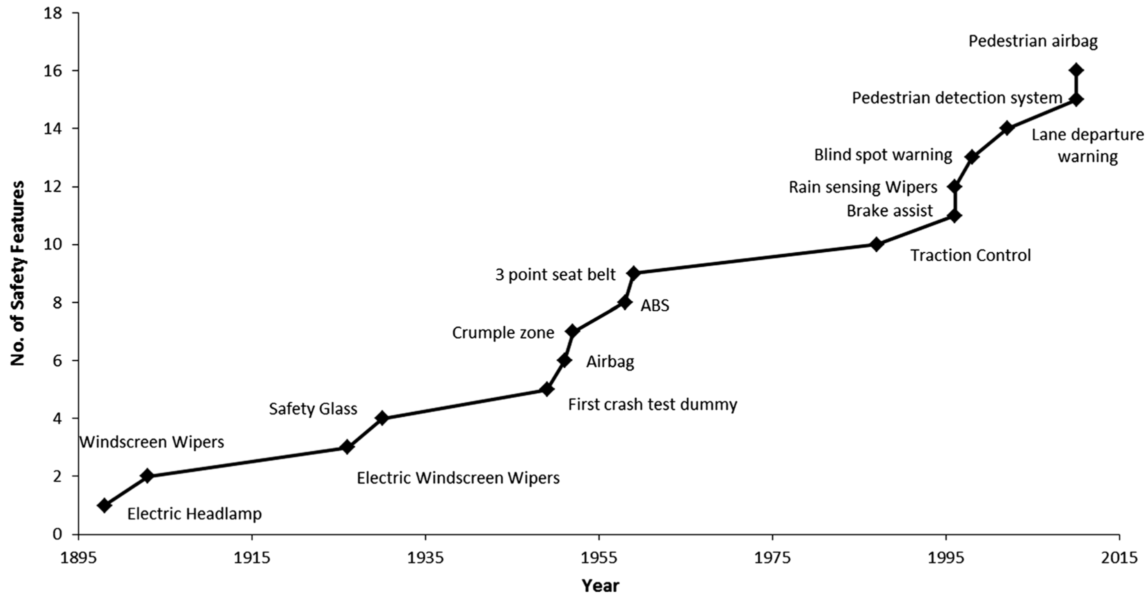
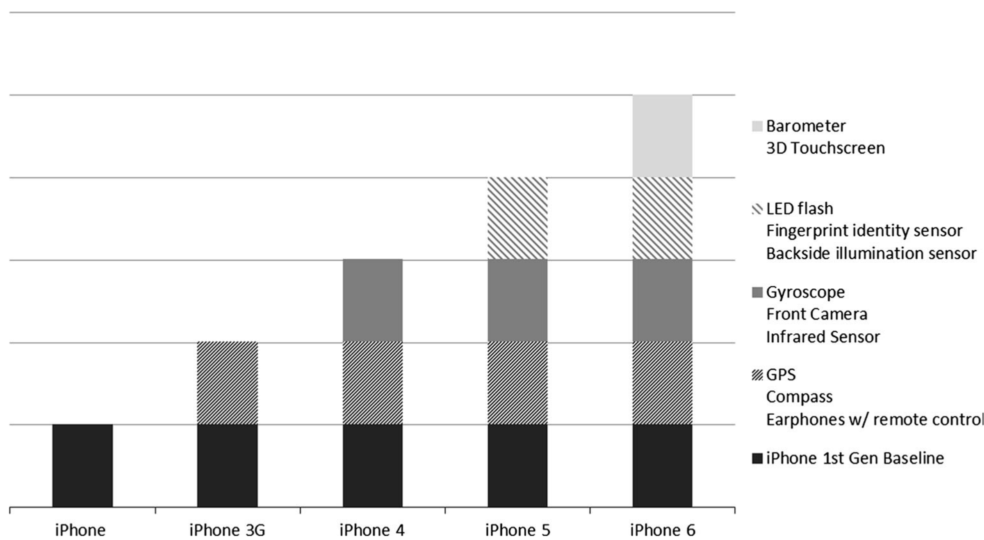


Fig. 1 Evolution of car safety features (Jackson 2013)

Fig. 2 Added functionality for every generation of the Apple iPhone (Apple 2015)



independence of functions which is said to produce inherently more robust designs (Suh 2001, p. 125, 126). A designer should first and foremost seek for an uncoupled or decoupled design and then, in adherence to the second axiom, minimize the information content. Slagle (2007) investigated the influence of the system architecture on the robustness and proposed 9 principles. Among those are the principles of "Independence" and "Simplicity" in accordance with the notion of Suh. However, it is not always practically possible to uncouple or decouple functions due to other conflicting DfX requirements. Furthermore, with respect to robustness the first axiom is not always true in reality as there are instances where a coupled design has a lower information content, which actually produces a higher probability of success and robustness.

Consider a machine that can position a drill with an accuracy of 0.02 mm ($\mu = 0$, $\sigma = 0.02$ mm) in the x direction and 0.005 mm ($\mu = 0$, $\sigma = 0.005$ mm) in the y direction. Let us also say that the tolerances on the position of the hole are ± 0.04 mm in the x and ± 0.03 mm in the y direction. If the workpiece is oriented square to the axes, the mapping from design parameter (DP) to functional requirement (FR) is diagonal and hence the design uncoupled (design 1). The probability of success is about $p = 95$ %. However, if the part is reoriented at an angle of about 30 degrees, the FR-DP mapping is coupled (design 2) and the probability of success rises to about $p = 97.5$ %, which is roughly a factor of 2 drop in failure rate (see Figs. 3, 4). This example provides proof that axiom 1 is not always true; however, the authors believe that axiom 1 is

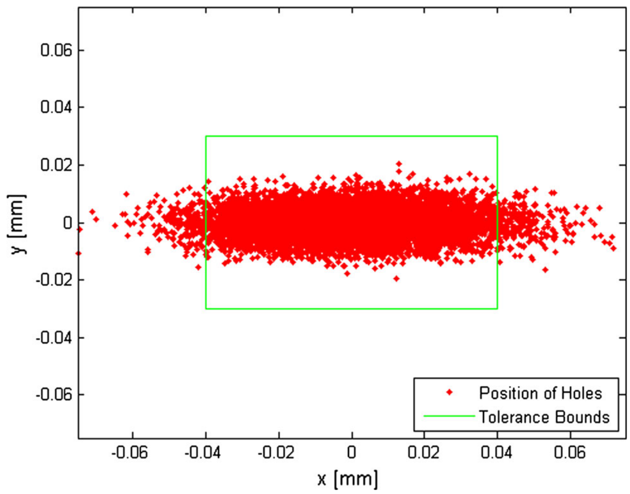


Fig. 3 Hole pattern for design 1 ($p = 95$ %)

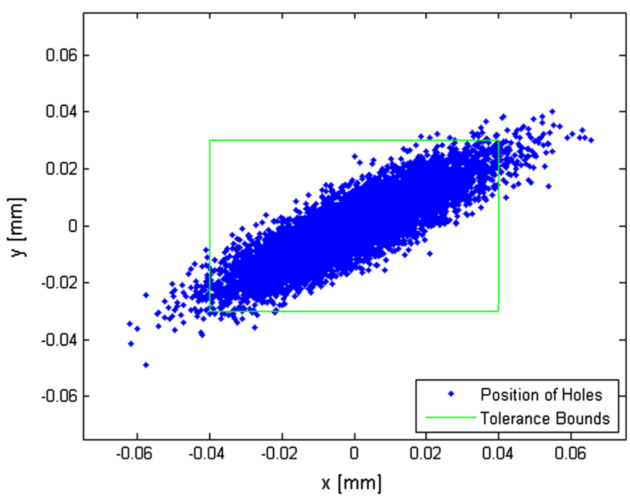


Fig. 4 Hole pattern for design 2 ($p = 97.5$ %)

still an incredibly valuable design *principle* (Ebro and Howard 2016) that should be used and taught despite the odd exception.

2 Research delimitation and methodology

The aim of this research is to investigate the link between the complexity of a design and its robustness. In order to understand this link first, several terms need to be defined. The robustness of a design is a key factor in achieving the desired quality of a product where yield $= f$ (robustness, variation). Therefore, in order to increase the yield, either the variation (coming from manufacturing, assembly, ambient conditions, time, load, the material and signal) needs to be reduced, or the robustness of the design (inherent in the product architecture, geometry and dimensions) needs to be increased.

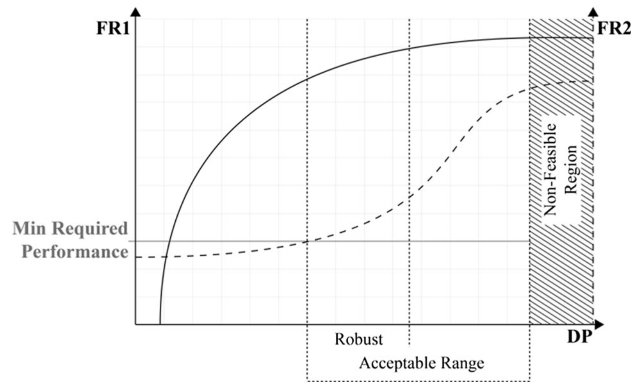


Fig. 5 Positive coupling of functions

In this research, we have chosen numerical analysis as a means for simulating the yield values since empirical data necessary to obtain meaningful statistical results would be unfeasible. The variation of the different design parameters has been modelled using a Monte Carlo simulation. By setting up the analysis in this way, it can be deduced that the designs that produced the greatest yield are therefore the most robust.

In order to create the designs, 250 different design architectures have been modelled based on the hierarchical probability model by Frey and Li (2008) (see the complex systems modelling approach later), each with differing complexity. In this paper, the authors define complexity to be related to the degree of coupling of the functions in the design (directly related to axiom 1) (Summers and Shah 2010) and the level of contradiction of the couplings. The definitions for coupling and contractions are best laid out in a previous research by Göhler and Howard (2015) in the following:

- A coupling with low level of contradiction (positive coupling): When changing a design parameter can lead to improvements in both of its coupled functions (Fig. 5).
- A coupling with high level of contradiction (negative coupling): When changing a design parameter will only positively affect one of the coupled functions as the other will be negatively affected (Fig. 6).

From this theoretical basis, two main research questions (RQ) arise and are addressed in this article:

RQ1 Is there an association between the degree of coupling in a design and its robustness?

RQ2 Is there an association between the level of contradiction in a design and its robustness?

2.1 A practical example case

To illustrate the practical implication of contradicting and positive couplings, consider an automobile diaphragm

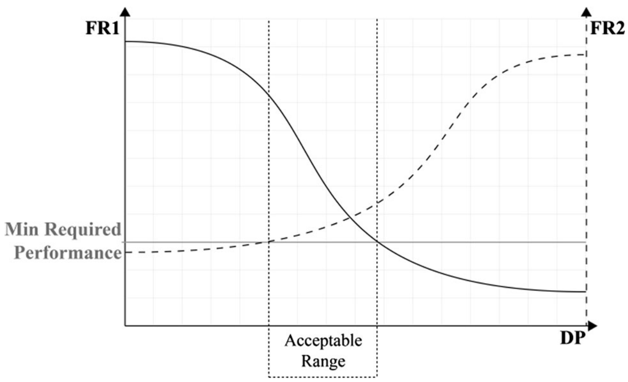


Fig. 6 Contradicting (negative) coupling of functions

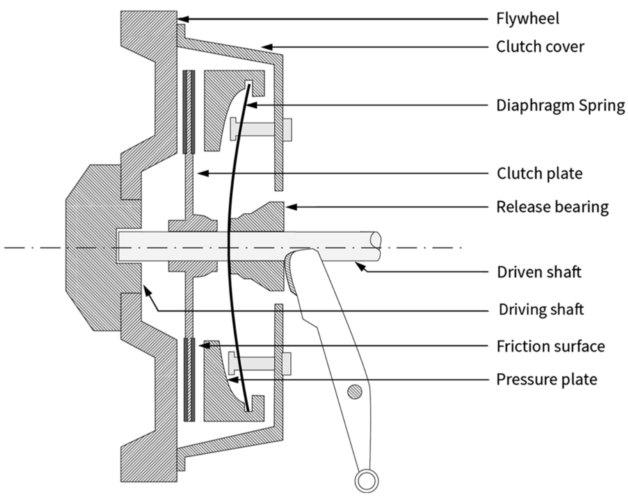


Fig. 7 Schematic of a diaphragm spring clutch. Adopted from Hillier and Coombes (2004)

spring clutch as shown in Fig. 7. The release bearing pushes the diaphragm spring inwards forcing it to buckle and release the pressure plate from pressing clutch plate and flywheel together.

Assuming the main functional requirements and design parameters to be the ones listed in Table 1, a simplified model using response surface methodology (RSM) (Box and Wilson 1951) yields the governing Eqs. (1–5).

$$T = -69.9 + 0.01 \cdot k + 504.4 \cdot s + 121.0 \cdot r_i + 139.2 \cdot r_o \tag{1}$$

$$F = -247.5 + 0.1 \cdot k + 5068 \times t \tag{2}$$

$$R = 0.13 - 0.6 \cdot 10^{-5} \cdot k - 0.64 \cdot t \tag{3}$$

$$W = 0.002 - 0.6 \cdot 10^{-8} \cdot k - 0.06 \cdot t + 0.04 \cdot r_i + 0.005 \cdot r_o + 0.1 \cdot 10^{-6} \cdot kt - 0.12 \cdot r_i r_o \tag{4}$$

$$c = -29562 - 10900 \cdot r_i + 33724 \cdot r_o + 2.6 \cdot 10^6 \cdot tr_o + 16 \cdot r_o \rho \tag{5}$$

Table 1 List of FRs and DPs for diaphragm clutch example

Functional requirements (FR)	Design parameters (DP)
Transmittable torque (T)	Diaphragm spring constant (k)
Force to disengage clutch (F)	Thickness of friction surface (t)
Responsiveness of clutch (R)	Friction surface inner radius (r_i)
Wear (W)	Friction surface outer radius (r_o)
Heat capacity of friction surface (c)	Friction surface density (ρ)

$$\begin{bmatrix} T\uparrow \\ F\downarrow \\ R\downarrow \\ W\downarrow \\ c\uparrow \end{bmatrix} = \begin{bmatrix} x\uparrow & x\uparrow & x\uparrow & x\uparrow & 0 \\ x\downarrow & x\downarrow & 0 & 0 & 0 \\ x\uparrow & x\uparrow & 0 & 0 & 0 \\ x\uparrow & x\uparrow & x\downarrow & x\uparrow & 0 \\ 0 & x\uparrow & x\downarrow & x\uparrow & x\uparrow \end{bmatrix} \begin{bmatrix} k \\ s \\ r_i \\ r_o \\ \rho \end{bmatrix} + \overrightarrow{\text{constant}} \tag{6}$$

In linearized and simplified form, the functional dependencies of the five main functions of the clutch (Eqs. 1–5) can be summarized using Suh's design matrix (DM) either quantitatively using partial derivatives or qualitatively as shown in Eq. (6). The arrows next to the FRs and the entries in the DM show the desired tendency of the value for the FRs and associated DPs. The design is coupled and is not easy to decouple or uncouple without changing the whole concept. However, since many of the requirements tend in the "same direction" the couplings are supporting (positive) couplings with no negative impact. Only the force required to disengage the clutch is in contradiction to the other requirements. However, solutions with for example an increased length of the lever arm or a hydraulic actuation could decrease the maximum required force.

3 A complex systems model

3.1 Assumptions

A product or system usually comprises of multiple functions and sub-functions that interact and are more or less coupled through the structural realization of the product or system (compare to the simplified diaphragm spring clutch example with its five functions which are coupled through the design parameters). For the presented model, a system is defined by the governing equations of its functions. All information and dependencies between design parameters, noise factors and functional outputs are assumed to be known. However, for real-world examples, this would be unrealistically resource intensive. The probabilistic modelling approach used in this study enables the investigator to generalize from a population of systems, but also easily alter assumptions of the model to match new findings and to check the robustness of the results. It is further assumed that the random parameter set $x_1 \ldots x_n$ is a valid solution to the design problem and all m functions are satisfactory fulfilled in that point. An optimization for maximum robustness is out of scope for this study. In a real design situation, there would also be weighting factors for each function meaning certain functions are more important or critical than others. The nature of the functions may also differ, some being more binary in nature, either functioning or non-functioning, where others would have a continuous spectrum of performance. For the purpose of this study, it is assumed that all functions are equally weighted and have a continuous nature. It is also assumed that the relative variation is the same for all influencing factors.

3.2 Model characteristics and set-up

In a previous study, Frey and Li (2008) adapted the hierarchical probability model (HPM) developed by Chipman et al. (1997) to assess the effectivity of parameter design methods. The HPM is solely a model for single functions and has in this work been extended for complex products and systems. Looking only at a small number of systems can be misleading since there are examples for complex but robust (aero engines, see also Carlson and Doyle 2000) but also simple and non-robust systems (GM ignition switch Eifler et al. 2014). The purpose of the surrogate model presented in the following is to be able to analyse a population of systems in a quick and inexpensive manner to be able to probabilistically assess the association between complexity and robustness. The model builds upon the nature of functional dependencies as observed in real-world systems. Three main characteristics and regularities can be seen from empirical data that have also widely been used in the design of experiment (DoE) context (see for example Box and Meyer 1986; Wu and Hamada 2011).

1. Sparsity of effects: Experiments have shown that "the responses [of functions] are driven largely by a limited number of main effects and lower-order interactions in most of the systems, and that higher-order interactions usually are relatively unimportant" (Kutner et al. 2004). In other words, there are usually only a small number of factors or parameters in systems that are actually influencing the performance of the functions. These are called to be "active" (Lenth 1989). This follows along with the well known Pareto's principle, also commonly referred to as the 80/20-rule stating that 80 % of the effects comes from 20 % of all influencing factors. In terms of modelling, this characteristic reduces the complexity and eases the representation of a function.
2. Hierarchy: Another common observation is that main effects are typically stronger than second-order interactions which are usually larger than third-order interactions and so on (Wu and Hamada 2011).
3. Inheritance: Empirical data reveal that interaction effects are more likely to be active if the interacting parameters' main effects are active (Wu and Hamada 2011).

To capture the entire product or system, which can be seen as a set of coupled functions, the model of Frey and Li (2008) has been extended. Equations (7) through (14) describe the main structure of the hierarchical probability systems model (HPSM). The HPSM describes functional response hyper-surfaces of multi-factor–multi-function systems that reflect observed functional regularities of sparsity, hierarchy and inheritance. In the way it is set up, it allows the investigator to adjust model parameters and probabilities to match assumptions and empirical data.

The hierarchical probability model by Frey & Li has been augmented by a functional dimension. There are m functions in a system with the ith function's performance $y_l(x_1, \ldots, x_n)$ expressed by a third-order polynomial equation that covers the effects of all n parameters $x_1 \ldots x_n$ and their interactions up to third order (Eq. 7). Modelling up to the third order is a sensible way of covering the most common effects without over-complicating the model. $x_1 \ldots x_n$ are the influencing parameters to the entire system (Eq. 8). These can be design parameters or part properties that can be controlled by the designer or environmental effects outside of the control of the engineers. In contrast to the model by Frey and Li, the differentiation between design parameters and noise factors is not necessary, since the analysis of couplings and contradictions is independent of the nature of the influencing factor. However, the distinction can easily be reintegrated to the model. For the remainder of the article, design parameters and noise factors will be referred to as influencing parameters (IPs).

The IPs are described by $\bar{x}$, a vector of continuous variables each randomly assigned between 0…1 to be able to vary the parameters for the assessment of the system robustness. The hierarchical probability model by Frey & Li has only two levels [0, 1] for x. It reflects the original experiments the model is based on, which chose the candidate range for x to cover the highest and lowest anticipated x. The experimental error from observations ε is irrelevant for this model and has been omitted. The probability p that a main effect is active $(\delta_i = 1)$ is described by Eq. (9). p is a probability value that incorporates the sparsity characteristic to the system. Equation (10) and (11) provide the probabilities that second- and third-order effects are active dependent on their parental main effects' activity. This introduces the characteristic of inheritance to

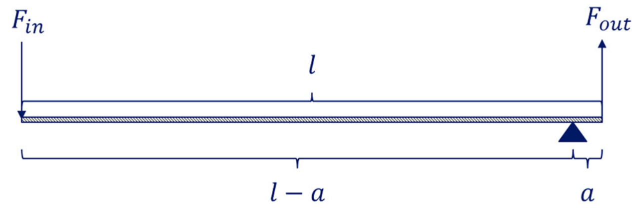


Fig. 8 Modelling the outgoing force $F_{\text{out}}(a)$ in a principle lever design with a third-order polynomial equation for small a gives (theoretically unbounded) high values for β_a

the system. Lastly, Eqs. (12–14) prescribe the β coefficients, i.e. the magnitudes of the effects on the functional output y, dependent on the associated effect being active or not ($\delta = 1$ or $\delta = 0$, respectively). As opposed to IPs, the effect magnitudes solely depend on the underlying natural laws and are therefore theoretically unbounded (see example Fig. 8). To reflect that, the coefficients are random normally distributed values with mean $\mu = 0$ and variance $\sigma^2 = d^2$ for active effects and 0 for inactive effects. Note that even active effects can have insignificant effects on the function since the mean of β is set to zero. Inactive effects have been omitted for this model opposed to the underlying model to avoid coupling in all possible parameters and allow for independence of the functions in the system as this is good design practice. Depending on the investigation, the constant β_0 can be chosen to ensure non-zero or positive values of y or simply be set to zero without loss of generality. The hierarchical structure of effects is described by Eqs. (13) and (14) reducing the second- and third-order effects by $\frac{1}{s_1}$ and $\frac{1}{s_2}$, respectively.

$$y_l(x_1, x_2, \ldots, x_n) = \beta_{0_l} + \sum_{i=1}^{n} \beta_{i_l} x_i + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \beta_{ij_l} x_i x_j + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \sum_{\substack{k=1 \\ k>i \\ k>j}}^{n} \beta_{ijk_l} x_i x_j x_k \tag{7}$$

$$l \in 1\ldots m$$

$$x_i \in \{0\ldots1\} \quad i \in 1\ldots n \tag{8}$$

$$\Pr(\delta_i = 1) = p \tag{9}$$

$$\Pr(\delta_{ij} = 1|\delta_i, \delta_j) = \begin{cases} p_{00} & \text{if } \delta_i + \delta_j = 0 \\ p_{01} & \text{if } \delta_i + \delta_j = 1 \\ p_{11} & \text{if } \delta_i + \delta_j = 2 \end{cases} \tag{10}$$

$$\Pr(\delta_{ij} = 1|\delta_i, \delta_j, \delta_k) = \begin{cases} p_{000} & \text{if } \delta_i + \delta_j + \delta_k = 0 \\ p_{001} & \text{if } \delta_i + \delta_j + \delta_k = 1 \\ p_{011} & \text{if } \delta_i + \delta_j + \delta_k = 2 \\ p_{111} & \text{if } \delta_i + \delta_j + \delta_k = 3 \end{cases} \tag{11}$$

$$f(\beta_i|\delta_i) = \begin{cases} 0 & \text{if } \delta_i = 0 \\ N(0, d^2) & \text{if } \delta_i = 1 \end{cases} \tag{12}$$

$$f(\beta_i|\delta_i) = \begin{cases} 0 & \text{if } \delta_i = 0 \\ N(0, d^2) & \text{if } \delta_i = 1 \end{cases} \tag{13}$$

$$f(\beta_{ijk}|\delta_{ijk}) = \frac{1}{s_2} \begin{cases} 0 & \text{if } \delta_{ijk} = 0 \\ N(0, d^2) & \text{if } \delta_{ijk} = 1 \end{cases} \tag{14}$$

3.3 Types of functional requirements

There are three types of functional requirements as described in (Taguchi et al. 2005)—maximum is best, minimum is best and nominal is best. The first two differ only in the sign and can be described in the same manner. These requirements are functionally bound only by a minimum (for maximum is best) or maximum (for minimum is best) requirement. However, physical constraints limit the maximum performance. An example for a minimum-is-best requirement is the weight of an airplane. The weight determines the fuel consumption and the lift needed. However, since a certain payload capability is required which again requires a certain lift and thrust the structural rigidity sets the lower bound for the empty weight of the airplane. An example for a maximum-is-best requirement is a simple pair of scissors where the length of the lever arm determines the cutting force. The lower limit of the size of the pair of scissors is set by the minimum required cutting force, the upper bound by the sheer size and ergonomics. Nominal-is-best requirements are functionally constraint on the upper and lower bound. A push button of a device, for example, should not be too easy or too hard to push since the user would associate both with a malfunction.

In the presented surrogate system model, the functions have requirements of the type maximum is best and minimum is best. Nominal-is-best requirements can be modelled as two separate functions one minimum is best, the other maximum is best with the same set of beta coefficients.

4 System evaluation

The developed surrogate model realistically describes a product or system with multiple functions and multiple influencing parameters. For this study, the system properties of interest are the complexity, i.e. the couplings and their level of contradiction, and the robustness. However, the model is not limited to complexity and robustness studies but can also be used for other investigations like optimization or design of experiments investigations.

4.1 Coupling and contradiction

A system as described in the presented model consists of multiple functions with multiple influencing parameters and their interactions. A common way to measure the complexity of the system is to evaluate the degree of coupling between the single functions, i.e. how many parameters are shared and what the influence of these parameters on the individual function is (Summers and Shah 2010). In axiomatic design (AD), Nam P. Suh distinguishes between three different types of systems and stresses the importance of the independence of functions for a predictable and high performance (design axiom 1).

1. Uncoupled systems
2. Decoupled systems
3. Coupled systems

However, no further distinction between systems of the same type is made on the conceptual level. Meaning that in cases where uncoupling or decoupling of the system cannot be achieved due to, for example, other DfX constraints, there is no means to further screen and compare the goodness of concepts. Suh's second design axiom, the information axiom, aims at the probability of achieving the required performances of the designed functions, which needs further and more detailed insights about the requirements on the one hand and the production capabilities on the other hand. A sensible extension of the independence axiom is to assess a system's complexity by evaluating the level of contradiction imposed onto the design, as discussed earlier in this paper.

In the presented study, the contradiction of a function in a system is described by the comparison of the influences γ_{ijk} of the single parameters on the different functions (Eq. 15). For this purpose, the weighted ratio was taken, reflecting the correlation of two functions in a particular parameter. The contradiction c_{ijk_l} of a function l with respect to a parameter $x_i x_j x_k$ is then defined as the maximum of the weighted ratios evaluated against all other functions w (Eq. 16). Note that there is minus sign to get a positive contradiction value.

$$\gamma_{ijk_l} = \frac{\beta_{ijk} x_i x_j x_k}{\sum_{i=1}^{n} |\beta_{i_l}| x_i + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} |\beta_{ij_l}| x_i x_j + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \sum_{\substack{k=1 \\ k>i \\ k>j}}^{n} |\beta_{ijk_l}| x_i x_j x_k} \tag{15}$$

$$c_{i_l} = \max_{\geq 0}\left(-\gamma_{i_l} \frac{\gamma_{i_l}}{\gamma_{i_w}}\right); c_{ij_l} = \max_{\geq 0}\left(-\gamma_{ij_l} \frac{\gamma_{ij_l}}{\gamma_{ij_w}}\right); c_{ijk_l} = \max_{\geq 0}\left(-\gamma_{ijk_l} \frac{\gamma_{ijk_l}}{\gamma_{ijk_w}}\right) \tag{16}$$

The highest possible value of contradiction in an IP is therefore $c_{ijk_l} = 1$ in the case that two functions share the same IP which accounts for 100 % of the functions' performance with opposite signs on the betas and therefore opposite requirements for this parameter or property. To describe the contradiction of a function, the sum is taken over all the individual contradictions in the IPs (Eq. 17).

$$c_l = \sum_{i=1}^{n} c_{i_l} + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} c_{ij_l} + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j>i}}^{n} \sum_{\substack{k=1 \\ k>i \\ k>j}}^{n} c_{ijk_l} \tag{17}$$

As for the contradiction value of functions to single IPs, the function contradiction c_l is bounded to 1 (or 100 %). $c_l = 100$ % relates to a fully contradicted function meaning that the function shares all of its IPs with other functions with entirely contradicting requirements towards the IPs. To evaluate the contradiction level of a system, the most contradicted function was taken (Eq. 18).

$$c_{Sys} = \max(c_l) \tag{18}$$

The example of the diaphragm spring clutch introduced in Sect. 2 yields a contradiction value of 0.7. The force to disengage the clutch (F) and the responsiveness (R) have strongly contradicting requirements with respect to the relevant IPs (k and t). However, as mentioned before the force to disengage the clutch can be addressed by a supporting function like a lever arm or hydraulic actuator. This essentially decouples the functions leading also to a lower contradiction score. Neglecting the disengagement force as a function leads to a contradiction value of 10 %.

It has to be noted that this is a simplification for the description of a system's contradiction level to ensure applicability in practice. There are instances where couplings and contradictions span multiple functions complicating the metric significantly.

4.2 Robustness

The robustness level of a product or system describes its functional insensitivity to variation of any kind whilst satisfactory meeting all functional requirements. The sources of variation can be categorized in manufacturing, assembly, load, environment, material, signal and time-dependent variation (Ebro et al. 2012). Robustness can be evaluated in many ways (Göhler et al. 2016). However, most metrics to describe robustness only address single functions. Among those are for example, the signal-to-noise ratio (Taguchi et al. 2005), derivative-based and variance-based as well regression-based sensitivities indices (Saltelli et al. 2008). In robust design optimization (RDO), this trade-off problem is addressed with multi-objective optimization algorithms. For example, Bras and Mistree (1993) utilize the methodology of compromise decision support problems (cDSP).

For this study, the evaluation of the system robustness is based on the idea that a robust system is less sensitive to ingoing variation and therefore has a larger design space also called common range which is the overlap between the design range and the system range (Suh 2001). Monte Carlo analysis (MCA) is used to alter all influencing parameters simultaneously in order to cover the entire system range. However, the definition of the common range is dependent on a "goodness" criterion for the systems' individual functional performance. Using this criterion to judge if a parameter set leads to the system being acceptable or unacceptable is similar to reliability assessments where a system can also only have two states: working or failed. The number of successes in the MCA is a measure of how big the common range is and therefore how robust the system is to variation. In the remainder of this paper, we will refer to this robustness score as the yield Y.

The MCA comprises of b iterations (trials) where the parameters $x_1 \ldots x_n$ are varied randomly in a specified interval v_{DP} for allowed variations to derive the varied parameter set $x_i^{'}$ (Eq. 19). The performance ratio pr_l for the individual functions y_l is computed and compared to the yield criterion z (Eqs. 20 + 21). If the performance ratio is greater than or equal to the yield criterion, this iteration (in design terms: combination of varied parameters) is consider a "success". As discussed earlier in this article, only max-is-best and min-is-best requirements are taken into account for this study. In this case, z can be interpreted as minimum required performance relative to the nominal performance. The yield, i.e. the ratio of successes to trials, is normalized with the number of influential factors a in the system (Eqs. 22 + 23). Even though a parameter is active, its contribution can be very low. By normalizing with the number of influencing factors, the robustness scores can be made comparable.

$$x_i^{'} = \left[\left(1 - \frac{v_{DP}}{2}\right) + \text{rand} \cdot v_{\text{DP}}\right] \cdot x_i \tag{19}$$

$$\text{pr}_l = \frac{y_l(\vec{x}') - y_l(\bar{x})}{y_l(\bar{x})} \tag{20}$$

$$\text{success} \leftarrow \text{pr}_l \geq z \text{ for all } l \tag{21}$$

$$Y = \sqrt[a]{\left(\frac{\#\text{ of successes}}{\#\text{ of trials}}\right)} \tag{22}$$

$$a = \#\text{ of } x_{ijk} \,\Big|\, \frac{|\beta_{ijk_l}| x_{ijk}}{|\beta_{ijk_l}| \vec{x_{ijk}}} \geq \frac{1}{\#\text{ of Active Paramters}} \tag{23}$$

5 Model execution

MATLAB is used to compute a data set of q systems with the presented hierarchical probability system model and to evaluate their functional contradiction and robustness. Analysing a population of systems yields the advantage to detect trends and correlations. Due to the probabilistic set-up of the model there is a chance of "zero" functions where all coefficients β are zero for a function. In that case, the product or system would fail to accomplish one of the required functions. Those systems are considered incomplete and erased from the data set. Furthermore, there is a chance for the parameter set $\bar{x}$ being the only solution for $z = 0$ and low numbers of influencing factors. These cases have also been disregarded.

The values for the probabilities and factors for the single functions in the model have been adapted from Frey and Li (2008), who investigated various empirical examples to extract those, to ensure the link to real-world systems. Table 2 states all probabilities and factors used in the model.

Given the probabilities in Table 2, the system model has been set up for $n = 5$ influencing parameters and $m = 5$ functions in a population of $q = 250$ systems. These model parameters have been chosen to keep the computational effort to a reasonable extent whilst ensuring well distributed data points across the whole range of contradiction and level of robustness and therefore ensuring the power of the data. The dependence of the selected number of influencing parameters and functions on the outcome will be investigated and discussed later in the paper. The MCA sample size has been selected to $b = 1000000$ following a study of the convergence for the slope and the intercept in the linear regression model (for the case $v_{\text{DP}} = 10\,\%$, $z = 0$) as a balance between computational time and accuracy (see Fig. 9).

6 Results

6.1 Association between coupling and robustness

Figure 10 shows a scatter plot of the normalized yield and therefore of the system robustness against the number of couplings in a system for $q = 250$ simulated systems with a uniformly distributed variation $v_{\text{DP}} = 10\,\%$ in the IPs and

Table 2 Model parameter

$p = 0.41$	$p_{00} = 0.0048$	$p_{001} = 0.035$	$s_1 = 3.6$
$p_{11} = 0.33$	$p_{111} = 0.15$	$p_{000} = 0.012$	$s_2 = 7.3$
$p_{01} = 0.045$	$p_{011} = 0.067$	$d = 10$	$\beta_0 = 0$

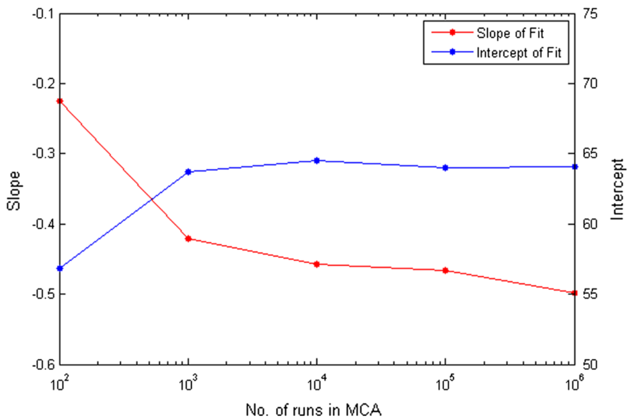


Fig. 9 Convergence analysis

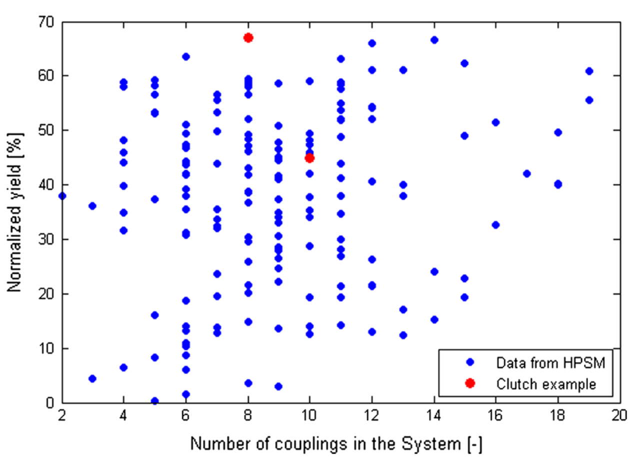


Fig. 10 Scatter plot of normalized yield against no. of couplings

a yield limit of $z = 0$. In the context of manufacturing variation, a normal distribution is often used to reflect the nature of the variation. With the focus on the system and common range, i.e. the robustness, a uniform distribution of the variation in the IPs was chosen to cover the system range as efficiently as possible. Two data points for the example of the diaphragm spring clutch (with and without the function for the disengagement force) have been added to the plot to illustrate the connection to a real-world design example. The Pearson's and Spearman's tests for independence have been conducted to quantify the association. With p values of 0.13 and 0.11, respectively, the tests suggest independence. That means that considering

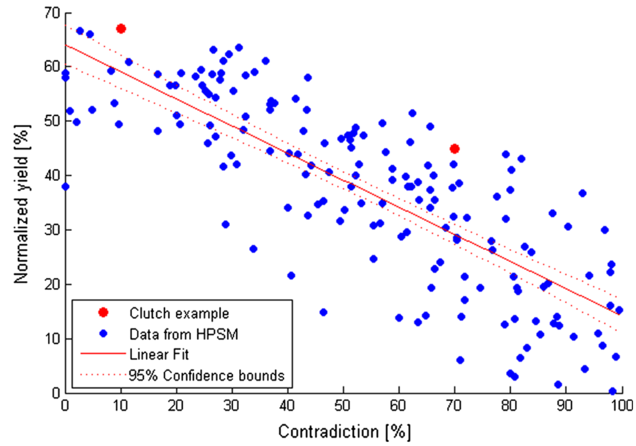


Fig. 11 Association between normalized yield and contradiction

the number of couplings alone does not give any insights to how robust a system is, addressing Research Question 1.

6.2 Association between functional contradiction and robustness

The scatter plot in (Fig. 11) shows the normalized yield against the functional contradiction as defined in the previous section for the same model run as before. To describe the association, the linear least square fit (Eq. 24) with its 95 % confidence bounds is included in the plot. Again, the data points for the example of the diaphragm spring clutch have been added to the plot.

$$\begin{aligned} &f(c_{sys}) = p_1 \cdot c_{sys} + p_2 \\ &\text{with} \\ &p_1 = -0.50 \\ &p_2 = 64.08 \end{aligned} \tag{24}$$

As can be seen from the scatter plot (Fig. 11), there is strong association between the level of contradiction in the functional requirements and the yield, i.e. the robustness of the system. With a p value of the F-statistic of 1.4e−36, the association is statistically significant. The Pearson's and Spearman's tests confirm this. Also, the 95 % confidence bounds do not include a zero slope, which would potentially mean independence. This result addresses Research Question 2.

6.3 Sensitivity to assumptions and model set-up

To verify the validity of the outcome and the independence to the model assumptions, some variations of the model have been investigated. Table 3 summarizes the model variants with their parameters and results.

As can be read off from Table 3, the association between the level of contradiction and the normalized yield

Table 3 Model variants

Variant	n	m	v_{DP}	z	Intercept	Slope	p value
Baseline	5	5	0.1	0	64.08	−0.50	1.4e−36
1	10	10	0.1	0	63.59	−0.33	1.0e−8
2	10	5	0.1	0	79.27	−0.36	1.8e−32
3	15	5	0.1	0	85.02	−0.24	2.6e−28
4	5	5	0.3	0	65.50	−0.51	1.2e−33
5	5	5	0.1	−2.5 %	70.12	−0.23	7.9e−20
6	5	5	0.1	−5 %	75.36	−0.11	1.4e−5
7	5	5	0.1	−7.5 %	84.75	−0.07	0.0005
8	5	5	0.1	−10 %	91.01	−0.04	0.12

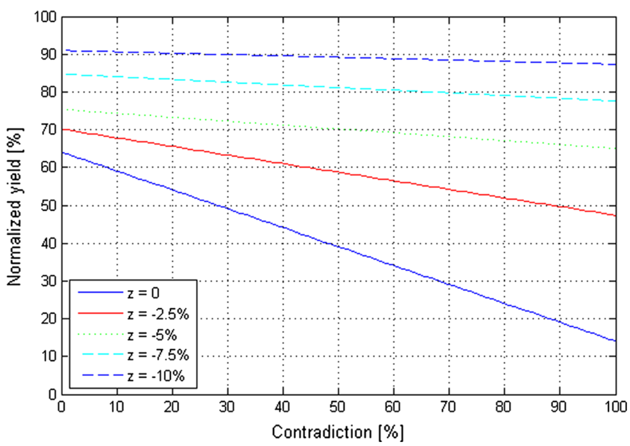


Fig. 12 Association between normalized yield and contradiction dependent on yield criterion z

is statistically significant for the model variants 1–7. In particular, the results show that the association holds also for systems with higher numbers of IPs n and functions m. Furthermore, the results from variant 4 suggest that the association is independent of the setting of the variation interval v_{DP}. However, the yield is strongly associated with the minimum required performance of the functions z. Since main effects with linear correlations to the functional performance are most likely and most powerful in the presented model, it is expected that for decreasing yield limits to equal or close to the magnitude of the ingoing variation v_{DP}, the yield increases and becomes independent of the level of contradiction. In simple terms, this means that as the specification window becomes wider, finding a design solution becomes easier and easier with a huge range of values to choose from. At a certain point, the specification windows are so large that the contradictions cause a relatively minor limitation to the parameter selection range and therefore have little impact on the yield. The results for variants 5–8 confirm this. Figure 12 shows the linear fits for a decreasing yield limit $z = 0 \ldots -0.1$. The ingoing variation is in all cases $v_{DP} = 10\,\%$. All other model parameters are also kept.

7 Discussion

Various scholars have investigated the relation between robustness to variation and complexity. However, there is no universal definition of complexity, and therefore, the studies had often different foci and levels of detail. One of the most influential frameworks in this field is axiomatic design, as discussed in this paper. Suh (2001) defines complexity "as a measure of uncertainty on achieving the specified FRs". The metric of the information content, which is defined as the logarithm of the inverse of the probability of success, is used both as metric for robustness but also complexity (El-Haik and Yang 1999). Magee and de Weck (2004) describe a complex system as "a system with numerous components and interconnections, interactions or interdependence […]". In accordance with this definition, some complexity metrics can be found in the literature that are based on the part and interface count as well as the number of part and interface types (Slagle 2007). These, however, are very simplified metrics and not appropriate to be used in the context of robustness due to the lack of the functional dimension. In the original robust design approach by Taguchi, system complexity plays a minor role. Implicitly, a less complex design can easily be optimized in the parameter design phase. On the other hand, a certain complexity is necessary to be able to find more robust parameter settings (Taguchi et al. 2005). Taguchi's view on complexity, however, refers therefore more to the sheer number of parameters. Summers and Shah (2010) distinguish between complexity metrics based on the size ("information that is contained within a problem"), coupling ("connections between variables at multiple levels") and solvability (the difficulty of solving a design problem) for the evaluation of parametric and geometric embodiment design problems (see also Braha and Maimon 1998). In this study, we define complexity through the degree of coupling and the level of contradiction between functional requirements. This is an extension of the ideas of the independence axiom. Suh presents a mathematical argumentation showing that for deterministic worst case considerations, the allowable variations in the design parameters ΔDP for specified variation limits of the functional requirements ΔFR are greatest for uncoupled designs (Suh 2001). However, these robustness calculations are dependent on set ΔFRs implying that all FRs are of the type nominal is best, which cannot always be assumed as shown in the clutch example case. Furthermore, an example for a more robust coupled design has been presented in the opening of this paper (Figs. 3, 4).

To the authors' knowledge, the presented study is the first attempt to relate robustness and complexity quantitatively using a model-based probabilistic approach. We found that for max- and min-is-best requirements, it is not the coupling of functions itself, but rather the level of contradiction of the couplings that influences robustness. As long as contradictions in the requirements imposed on the parameters, properties and dimensions of the system can be avoided, coupling does not inherently harm the robustness. Descriptive studies like the one by Frey et al. (2007) support this finding with an empirical analysis of complex systems. They assessed part counts and complexity of airplane engines against their reliability and found that despite the constantly increasing degree of coupling and integration, the reliability of aero engine improved. Braha and Bar-Yam (2007, 2013) studied the network topology of four large-scale product development networks. They defined coupling with the concept of assortativity, which describes the tendency of nodes (IPs in the case of engineering design networks) with high connectivity to connect with other nodes with high connectivity. Networks with high assortativity are inherently more complex which tends to reduce system robustness. Contradiction as defined in this study can be seen as a measure of assortativity in the domain of unipartite networks. Furthermore, it was found that systems are robust and error tolerant to variation in random nodes but vulnerable to perturbation in the highly connected central nodes ("design hubs") (Albert and Barabási 2002; Braha et al. 2013; Sosa et al. 2011). In the engineering design context, this refers to the necessity to control the design but also the variation of the most influential parameters with contradicting requirements (Braha and Bar-Yam 2004, 2007). Carlson and Doyle (2000) proposed and discussed the framework of HOT (Highly Optimized Tolerances). They argue that evolving complex systems which underwent numerous generations are extremely robust to designed-for variation, but "hypersensitive to design flaws and unanticipated perturbations". The increase in robustness is driven by continuous development and improvement including solving of known imperfections and contradictions. This view supports the results of the presented study. An implication of these findings is that the TRIZ contradiction matrix (Altshuller 1996) is likely to be a suitable method for increasing system robustness at a conceptual level. The method suggests that the contradicting parameters are the limiting factors of a design and inventive principles can be identified to overcome the contradictions "without compromise".

A limitation of the presented study is that as of now, the model features only maximum-is-best and minimum-is-best requirements. Nominal-is-best requirements have been neglected. To extend the insight to all types of requirements, further investigations are needed. Further, this study is based on the analysis of a population of complex systems generated with the model proposed in this paper. We found clear correlations between the level of contradiction and robustness. Whilst definite predictions for the robustness of single systems cannot be made, it can be concluded that the chance that a contradicted system is less robust is high.

8 Concluding remarks

In this study, we extended the hierarchical probability model by Frey and Li (2008) to model complex systems and their functional responses for the case of maximum-is-best and minimum-is-best requirements. The model was used to assess how a system's robustness to variation is influenced by design complexity in terms of the degree of functional coupling and the level of contradiction between the functional requirements.

In answer to Research Question 1, the correlation between the number of couplings in the system and the system robustness was found not to be statistically significant.

In answer to Research Question 2, a statistically significant association between the level of contradiction and system robustness was found ($p = 1.4\text{e}{-36}$) where an increase in contradiction is associated with a decrease in robustness.

These results have great implications on our understanding of the nature of complexity and robustness. Suh suggests two design axioms which can be, to an extent, "accepted without proof" (as per the definition of an axiom). The robustness claims of the independence axiom are based on assumptions about the fill of the design matrices and the nature of the functional requirements, which are not always fulfilled in real-world examples. The results in this study challenge Suh's theory about the negative impact of coupling in systems with max- and min-is-best requirements, stressing that it is actually the level of contradiction of the couplings that determines the level of robustness. Uncoupled designs are by definition free from coupling and therefore contradictions and as a result are inherently robust relative to coupled designs (in general). However, there are specific examples where this does not hold, since coupling can be used to reduce the number of influencing factors, it is possible to reduce the overall variability and therefore improve the robustness by the introduction of positive couplings (couplings without contradiction).

In practical terms, the knowledge of the association between system robustness and functional coupling can be used in early design stages. When the first concepts and embodiments are produced, engineers are often able to identify the most influential properties and dimensions for the performance of the single functions, making it possible to evaluate contradictions to a certain level. A robustness evaluation can therefore be conducted on the different concepts based on the level of contradiction identified within the concepts. Further, the design focus and control should lay on the coupled and contradicted parameters. However, for precise evaluations of functional performances, yield and reliability, detailed models and experiments are necessary. Knowing about contradicting and competing requirements provides insight into the robustness characteristics of complex products or systems that can be utilized to minimize risk and make more educated concept selections.

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The Translation between Functional Requirements and Design Parameters for Robust Design

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Abstract

The specification of and justification for design parameter (DP) tolerances are primarily based on the acceptable variation of the functions' performance and the functions' sensitivity to the design parameters. However, why certain tolerances are needed is often not transparent, especially in complex products with multi-disciplinary development teams. In those cases, tolerance synthesis and analysis get complicated which introduces ambiguities and difficulties for system-integrators and lead engineers for the objective decision making in terms of trade-offs but also in terms of an efficient computer aided functional tolerancing. Non-optimal tolerances yield potentials for cost improvements in manufacturing and more consistency of the functional performance of the product. In this contribution a framework is proposed to overcome the observed problems and increase the clarity, transparency and traceability of tolerances by analyzing the translation between the DPs and their influence on the final function.

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Keywords: Robust Design; Tolerances; Information Modeling; Dimensional Management; Variation Transmission

1. Introduction

Mechanical products and systems of all kinds are subject to variations in their parts' and assemblies' dimensions and forms, their materials, their use and their operation environment. However, despite these variations, products are expected to deliver their function and/or aesthetics to a predetermined extent and time to ensure customer satisfaction. To acknowledge the variation in the production phase, i.e. in manufacturing and assembly, part drawings usually contain tolerances on the single dimensions, forms and positions. In most cases these tolerances determine a large share of the cost of production but also of quality assurance. Tighter tolerances might require special production machinery, tooling, metrology equipment and drive the scrap and rework rate of a part; thus the effective analysis and assignment of tolerances as well as robust design can yield great cost saving potentials [1], [2].

The types and magnitudes of the tolerances, i.e. the size of the allowable ranges, are determined by the functional, technological and esthetical requirements of the product that shall be fulfilled. In highly complex (mechanical) products and systems that require multi-disciplinary development engineering teams (as for example jet engines that need specialists in Design, Fluids, Thermals, Structural Mechanics etc.), the relationship between tolerances and requirements often becomes complicated and non-transparent. This is especially the case when the outputs of one engineering discipline are inputs to another. When setting the tolerances, a whole patchwork of analyses of the influences of all kinds of variations develop where bonus tolerances and process capabilities are also considered in the allocation. Computer Aided Tolerancing (CAT) is utilized for tolerance synthesis and analysis [3], [4]. However, CAT is often limited to geometrical requirements like lengths, gaps and clearances as functional requirements [5]. The most common methods are tolerance chains and sensitivity analysis using experiments or simulations depending on the individual function. Due to the nature of multi-disciplinarity these analyses often stand separately and independently. An important challenge in a

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multi- disciplinary industrial application is that the engineers use different vocabularies for the requirement and problem specifications. Furthermore, for the specification of interface requirements often product characteristics (e.g. large width) are used instead of the required properties (e.g. high stiffness). As for the nominal dimensions that are being passed from discipline to discipline, the same happens to the tolerances and safety factors. The justification of tolerances is not very transparent making it difficult for system integrators and lead engineers to challenge the design and prioritize necessary additional analyses. Also, for drawings of parts that have been produced for years it is often the case that the justification of tolerances cannot be reconstructed and it is not understood what functions certain dimensions contribute to. In addition, the re-use of modules or components as part of a platform strategy may leave tolerance justifications running over multiple product lines. This all leads to a strong hesitation regarding changes to the parts due to unknown risks associated with those (see for example the GM ignition switch recall case [6]).

The translation between the design parameters (DPs) or external noise factors (NFs) and the functional requirements (FRs) is an established way to map the behavior of a product or system. The Robust Design Methodology (RDM) uses these transfer functions to derive sensitivities of functions to DPs and NFs to optimize the performance and predictability of the final product [2]. The setting of tolerances is directly linked to the sensitivity of the functions to the single DPs. RDM and the mapping between FRs and DPs are more or less explicitly done by the individual engineering disciplines. However, in the case of a complex and highly integral system, effects that go beyond a specific function or sub-function can be difficult to oversee. The mapping gets complicated and impractical in these instances making it difficult to have efficient tolerance design and allocation. “Information modelling is critical to the integration of design and tolerancing” [7].

The question arises of how the clarity and transparency of tolerances as well as their impact and severity on the final functional performance can be captured in a practical way.

In this contribution we address the encountered problem by proposing a framework on how to look at tolerances to support the specification and justification of tolerances for a robust design. Based on comprehensible decomposition and structuring of functional requirements and their design parameters a target-oriented communication between engineers of multi-disciplinary teams is supported. The framework enables the specification and justification of tolerances but also the setting of nominal dimensions across different disciplines and can give the basis for more advanced tolerance optimization within CAT.

2. Previous work

The idea of systematically mapping the dependencies of functions to design parameters and their tolerances is widely established in the engineering design community and is usually referred to as requirement or system decomposition. A framework that largely makes use of decomposition is Axiomatic Design (AD) by Nam P. Suh [8]. AD promotes not only the mapping between FRs and DPs but also the mapping from customer attributes (Customer domain) to the functional requirements and the mapping between design parameters and process variables in the process domain. The decomposition of the high level functional requirements and how these are addressed in the physical domain is realized by so called zigzagging between the functional and physical domain. With this, new evolving lower level requirements and design parameters are systematically established and a design solution generated. The function-means tree model as described by Hansen and Andreasen [9] works in a similar fashion arranging the functions and their realizations in a hierarchical manner. Söderberg and Johanneson [10] utilize function-means trees to detect potential tolerance chains to increase robustness. However, these techniques are more an idealized process that is often not practical, especially if the product is complex or solutions are being reused. Another framework that is more tailored towards the management of variation in design and manufacturing is the Variation Risk Management (VRM) framework by Thornton [11]. The framework is generally divided into three phases: Identification, Assessment and Mitigation. The identification of potential issues related to variation followed by the assessment of the associated risks as well as costs and the final mitigation of the issues with the most potential forms a holistic approach. In that way, trade-offs between design and manufacturing can efficiently and objectively be managed to improve the quality and cost of the final product. With respect to the systematical tackling of the issues, the identification phase comprising the collection of variation-sensitive requirements and the risk flow-down to understand the structure of the product are of high importance. “The risk flow-down is an iterative decomposition process that identifies a hierarchy of contributing assembly, subassembly, part and process parameters [12].” Dantan et al. [1] propose an information model capturing the causality of Manufacturing Process Key Characteristics and Part/Product Key Characteristics to manage manufacturing resources and tolerances. The House of Quality (HoQ) methodology in Quality Function Deployment (QFD) has a similar domain based structure as Axiomatic Design [13]. It maps the customer attributes through the parts and process domain to the production domain. The decomposition of the attributes is facilitated by relating the “whats” to the “hows”. “What” is the requirement and “how” is it addressed. The “hows” are turned into “whats” for every level of decomposition in a new “house”. The Integrated Tolerancing Process (ITP) as presented by Dantan et al. [7] addresses the functional decomposition of tolerances through geometrical requirements and decomposed functions. Howard et al. [14] proposed the Variation Management Framework (VMF) emphasizing the mapping of variation and sensitivities through the domains for robust design. Hansen [15] and Weber [16] presented further product and process representations describing the relationship between requirements and product characteristics considering external influences. Methods like FMEA (Failure modes and effects analysis) and RCA (Root conflict analysis) use decomposition techniques to find the root causes for failures or potential failures.

3. Translation between FRs and DPs – a proposal for a new framework

The frameworks and methods discussed in the previous section are widely accepted and have proven to be useful in design and failure analysis situations. However, for the daily engineering development work and especially the detailed tolerance design and analysis phase, frameworks like Axiomatic Design and the House of Quality are too generic and impractical for addressing the issues mentioned in the introduction. Tools like FMEA and RCA can be of an appropriate level of detail but are, however, too focused and therefore limited to failures. The VRM framework on the other hand gives a good guidance to break down the product key characteristics to the related process characteristics. However, VRM is limited to dimensions that can be measured on the shop floor and in the assembly line and is therefore very production focused. Abstract functional and emerging properties like “mechanical stiffness” or “efficiency” are not addressed.

The purpose of the proposed framework in this contribution is to adapt and extend the VRM to include functional and emerging properties of a product. With this, it is believed, the communication between different engineering disciplines regarding dimensions and their tolerance can be made more understandable, traceable and transparent also for non SMEs (subject-matter experts) like system integrators and managers. The derivation of the framework is driven by the question of how to map between functional requirements and design parameters most efficiently. The idea is to ease the mapping and therefore extent the existing methods described in Section 2. Consider the “easy” example of a cantilever beam with a rectangular cross-section, where the functional requirement is a specific maximum deflection δ_{max} at the far end under a load F. For this case an analytical expression can be derived as:

$$\delta_{\max} = \frac{F \cdot l^3}{3 \cdot E \cdot \frac{b \cdot h^3}{12}} \tag{1}$$

The equation includes all influencing dimensional, material and load parameters. A design engineer could now for example insist on a specific height h of the beam to limit the maximum deflection of the beam. With constraints maybe only on the length and the material of the beam, the actual interest is in the second moment of inertia I rather than only the height.

$$I = \frac{b \cdot h^3}{12} \tag{2}$$

A wrongly / too simplistic formulation of the requirement unnecessarily constrains the solution space and can cause a non-optimal dimensioning and tolerancing. This clarification eases the mapping between FR and DPs and increases the understanding of what properties are actually required. The complicatedness of the transfer function rises with the complexity and level of abstraction of the functional requirement and can hence also be reduced.

Figure 1 illustrates the mapping between a functional requirement and a contributing design parameter (for simplicity only one DP is shown, in most cases a FR is dependent on multiple DPs). As in the example of the deflection of the cantilever beam, it is often helpful for the communication and traceability not to map the FR directly to the corresponding DPs but introduce sub-functional requirements (SFRs) in between. Especially abstract FRs like for example efficiency and acceleration can have complicated dependencies with numerous DPs. Decomposition into SFRs can help to express actual requirements for a function.

The translation between FRs, SFRs and DPs can be done from the ‘selection of concept’ onwards. In the early phases the translation might be based on analytical descriptions and first order principles of the function. First statements about the importance and sensitivities of SFRs and DPs can be made. As the design matures the mapping can be detailed including data from experiments and simulations.

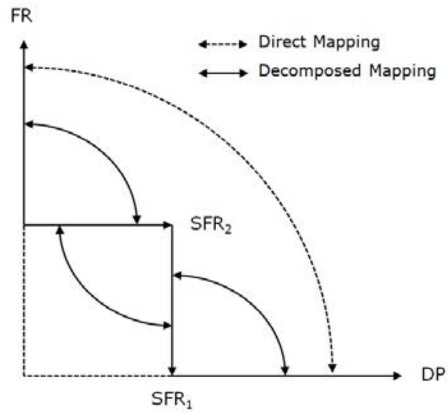

Figure 1: Mapping between FR and DP

To formalize the framework and the introduction of SFRs a bottom-up approach has been chosen to derive the different levels of SFRs starting at the sources of variation, which are dimensional, material, external (loads and environment) and time-related. Further, the P-Diagram (Figure 2) is used to structure the different sources of variation. The product is defined by its single DPs (control factors). This very basic level of definition is used on technical drawings of physical parts and assemblies. Nominal geometrical dimensions and form attributes as well as required material and surface properties are defined including their allowable deviations and tolerances. The most basic functional requirements are directly on these lowest level DPs and we define these as Level 1 SFR. Resulting from customer surveys, for example, a company developing a smart phone sets certain requirements on the width and length as well as the “feel” (material and surface) of the phone. These requirements are directly linked to the housing of the phone and are prescribed on its drawing. Level 2 SFRs combine properties of multiple dimensions, like required volumes or area moments, but also relative sizes and positions in assemblies. Examples for Level 2 requirements are the capacity of an engine and the position of a button on a phone.

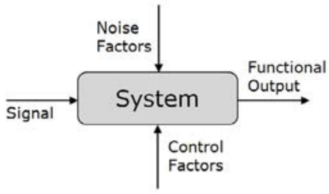

Figure 2: P-Diagram

The level of abstraction is further increased for the 3rd level SFRs. Combining dimensions and material properties yields for example part or assembly properties like weight, stiffness and rigidity. SFR levels 1-3 entail the physical properties of a product or system and build logically on top of each other. For example, to derive the weight of a part, its volume and density needs to be known, which again implies that all single dimensions are known. For level 4 SFRs external non material or geometrical factors, like for example temperature, load or flow, are included. Some physical phenomena are time dependent such as creep, wear and corrosion. The variable time is included in level 5 SFRs. All other SFRs and functional responses and properties of higher complexity can be derived as aggregations of level 1- 5. Level 6 comprises of all higher level functional requirements including advanced emerging responses like efficiency, power etc. Table 1 summarizes the proposed framework with examples for mechanical properties. Higher level sub-functional requirements are by inherent nature more complex and less restricting than lower level SFRs. The association of each tolerance to their respective SFR and functional origin in a database can increase the clarity, transparency and traceability and can support an efficient CAT.

Application

To ensure the applicability of a framework like the proposed decomposition of functional requirements, the Pareto Principle should be followed. Rather than having an exhaustive break down of all influencing parameters and properties of a function, the focus should be on the most influential characteristics and properties of a design towards the functional requirements. The idea of this framework and approach of looking at tolerances is to increase the understanding and traceability. Therefore, the highest meaningful level of SFR should be used to communicate acceptable ranges for the individual functions. In that way the design is also not being constrained more than necessary. Knowledge and experiences from previous projects as well as results from analyses can be utilized to formulate the SFRs. It shall be stressed here that usually no additional analyses and tests need to be run. The data that is anyway being produced for design, verification and validation shall be utilized to express the SFRs.

Table 1: Description of Sub-Functional Requirement Levels

	SFR	Sources of Variation	Examples (mechanical)
Control Factors (Design Parameters)	Level 1	Single Dimensions and Material Properties (Basic definitions on drawing)	• Geometrical dimensions • Forms (GD&T) • Material properties (Density, yield stress/strain, Young's modulus, conductivity, resistance…) • Surface finish
	Level 2	Multiple Dimensions	• Volume, Area • Aspect ratio • Moment of inertia • 2nd Moment of area • Assemblies (relative dimensions, positions, orientations, flushness, gaps, overlaps)
	Level 3	Dimensions & Material Properties	• Weight • Stiffness • Rigidity
Use (Signal & Noise Factors)	Level 4	Dimensions & External Factors	• Stress
		Material Properties & External Factors	• Thermal Expansion (relative)
		Dimensions & Material Properties & External Factors	• Thermal Expansion (absolute) • Bending, buckling, distortion • Compression
Time	Level 5	Dimensions & Material Properties & External Factors & Time	• Creep • Corrosion • Wear
Functional output (behavior)	Level 6	Emerging responses and properties (combining Level 1 – 5)	• Friction • Efficiency • Power, Energy

Once the SFRs for all functions are defined, they can be compared and analyzed by system integrators or lead engineers to make the trade-offs for working out the final tolerances of the dimensions on the part drawings. Design Structure Matrices can be used as a structured way to capture all SFRs.

4. Example – The Glue Gun

The proposed framework and way of thinking about tolerances shall be demonstrated in a simple example. Note that the advantages and usefulness of the proposed framework arise with a higher product complexity and multi-disciplinarity. The example is chosen to illustrate the general idea. Figure 3 shows the principle model of a glue gun [17]. By pulling the trigger (green) the grabbing arm (red) clamps the glue stick onto the sledge and subsequently drags it forward to feed the heating unit that finally dispenses the glue. Depending on the way of argumentation, the framework can be used in a bottom-up or top-down fashion. To investigate, for example, the origin or the functional impact of tolerances it is practical to review the SFRs bottom-up, whereas for the design and tolerance synthesis a top-down approach breaking down the functional requirements to SFRs using experience, analytics, experiments and simulations is appropriate. "Thought experiments" like the virtual deviation method [18] can also help to identify the most influencing parameters. For the glue gun example a top-down approach is demonstrated in the following. For simplicity reasons it is assumed that there are only two main functional requirements for the glue gun: 1) the application force for the user (for example 8 +/- 2 N) and 2) the precise and predictable delivery of glue (for example 0.5 +/- 0.1 ml/stroke). Table 2 summarizes the decomposition of the two functional requirements.

The application force is mainly driven by two phenomena: firstly the friction of all moving parts and secondly the general gearing of the mechanism itself.

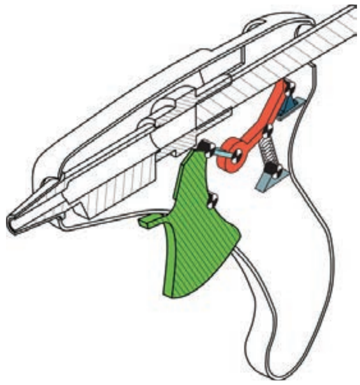

Figure 3: Glue Gun Principle Model

The friction is a complex phenomenon depending on the materials, the applied force but also on relative sizes, positions and orientations of the single parts. Another influence is the level of compliance in the system. Using the breakdown to SFRs as proposed in the previous sections helps to identify the actual attributes and properties influencing the application force for the glue gun and to prioritize further analyses as appropriate. For the allocation of tolerances, the constraints on the highest possible level of SFR should be used to constrain the design as little as possible.

Table 2: Functional Requirements Breakdown for Glue Gun Example

	Constant application force (+ no jamming)	Precise and predictable delivery of glue (Linear translation between trigger and feed)
Level 6	Friction of moving parts	Slip of glue stick: friction of hook to glue stick > rubber heater inlet to glue stick and vice versa for retraction
Level 5	n.a.	n.a.
Level 4	• Bending, buckling, distortion, deformation of mechanism parts	• Bending, buckling, distortion, deformation of mechanism parts
Level 3	• Stiffness of mechanism parts	• Stiffness of mechanism parts
Level 2	• Sledge width to rail width • Ø glue stick to Ø heater, Ø nozzle, Ø rubber hole, clamping arm length, Ø sledge pass through, Ø housing hole • Hole positions of joints • Alignment of sledge and rail (housing halves relative position) • Alignment of sledge and heater • Moments of inertia of mechanism parts • Aspect ratios of lever arms	• Ø pin to Ø hole of joint connections • Sledge width to rail width • Moments of inertia of mechanism parts • Gaps in joints (wiggle room) • Gap between rail and sledge • Aspect ratios of lever arms (gearing ratio)
Level 1	• Parts' E-modulus • friction coefficients • Spring constant • Dimensions of mechanism parts	• Parts' E-modulus • Dimensions of mechanism parts

In that way the design can also more easily be assessed and challenged by non-SMEs, i.e. system integrators and lead engineers. If, for example, bending and buckling of the mechanism turns out to have a major influence on the application force, the constraints and tolerances should be set and communicated on that level, ensuring the understanding for tolerances but also leaving design space to change the design and material while complying with the constraints on bending and buckling. The second main functional requirement, the precise and predictable delivery of glue, is dependent on the smooth and linear translation between trigger and feed sledge. The most important characteristics are the gearing of the mechanism, the level of compliance and the prevention of slip of the glue stick. Again, the highest level requirements should be selected to communicate the SFRs and to set the tolerances.

5. Discussion and concluding remarks

In this contribution we propose a new framework of how to translate between functional requirements and design parameters through sub-functional requirements to improve the specification and justification of tolerances. Expressing the sub-functional requirements leads to a less constrained design. Compared to traditional tolerancing frameworks that focus on interfaces and resulting positions and orientations of parts in assemblies [19], the presented framework captures also functional emerging properties taking material properties, external factors like forces and temperature as well as time related factors into account. Tolerance methods that do take functional responses into account are mostly concerned with tolerance analysis or allocation and optimization [4], which require very detailed models which, again lack transparency and traceability. With the proposed approach a clear traceability of tolerances can be ensured linking them to the respective SFRs, which can be done in a less complicated way than to the overall FR. The framework also yields potentials in improving the communication about and the finding of design trade-offs especially in multi-disciplinary designs as well as the extension of computer aided functional tolerancing to properties of higher abstraction. Positive impacts can also be seen on change management and propagation, design documentation including reasoning as well as motivation and decision support in terms of decision rational. Knowing the main influencing attributes and properties also helps robust design and design optimization. Furthermore, the SFRs can directly be compared to customer requirements and product specifications as well as potentially be used for testing and verification purposes.

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The Variation Management Framework (VMF) Tool for Robust Design

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Variation is omnipresent in production but also in the use phase and needs to be catered for in design. With the "Right-first-time" paradigm and the trend towards virtual verification and validation, the understanding of the functional behaviour and the impact of variation becomes critical. Given this, new demands emerge towards a holistic and metric-driven variation management and Robust Design, especially for complex products. Different methods and frameworks exist to tackle this challenge. However, a coherent and holistic tool is lacking to address this complexity. To overcome the challenge, the research presented in this contribution builds upon and extends the Variation Management Framework (VMF) by Howard et al. (2017). The proposed tool utilizes insights and analyses addressing system robustness and complexity to holistically evaluate robustness and support Robust Design throughout the development and production of complex products. The tool was presented and applied in a workshop at the Robust Design Day 2016 and successively further developed and tested in an in-depth case study. First experiences and feedback show promising results and point towards a great potential to support holistic Robust Design.

Keywords: Robust Design, Variation Management, Quality Engineering, VMF, Key Characteristics

1 Introduction

In recent years, products have gotten more and more complex thriving for integrated designs with a rising amount of functionality with optimized performance and physical space (Göhler, Frey, and Howard 2016; Maurer 2007). This trend can be seen for all kinds of products from insulin pens which integrate mechatronics to cars that become more and more autonomous. At the same time, competition on the market puts pressure on the individual companies to develop the products in as short time as possible leading to an increased use of virtual verification and validation techniques in order to avoid lengthy and expensive prototyping and physical tests. However, the design under uncertainty and the design to cope with variation stay a challenge, especially with reduced and late physical testing. Even though companies postulate and promote the "Right-first-time" philosophy, redesigns, product launch delays, problems with production ramp-up and product recalls are not uncommon (Ebro 2015). An acknowledged methodology to design products to be insensitive to variation not only to noise factors (type I robustness) but also to changes to the design itself (type II robustness) is Robust Design (Allen et al. 2006). However, the complexity of the product and the associated missing understanding of the functional behaviour create uncertainty regarding the impact and propagation of variation and make the implementation and application of Robust Design difficult. Challenges regarding the analysis and objective evaluation of the robustness of complex products hinder the continuous improvement, monitoring and prioritization of tasks throughout the development. Non-optimal designs and trade-offs are the consequence. Most quantitative Robust Design tools rely on very mature mathematical models and often only address single functions neglecting the product or system perspective (Göhler, Eifler, and Howard 2016). Problematic is also the organizational complexity of the development process with specialists from various areas including engineering, marketing, sales and production working together. The complexity makes it too complicated for single engineers to overlook the whole product, even though the information is available. Most analyses are conducted independently from each other building a patchwork of information that is oftentimes not shared between the different functions and departments, which is referred to as "Silo thinking" (Gmelin and Seuring

2014). It is the authors' perception and experience from numerous collaboration and student projects in industry that although Robust Design and Systems Engineering are widely acknowledged and applied, many problems related to variation that should supposedly not occur, are still present.

The Variation Management Framework (VMF) proposed by Howard et al. (2017) is seen as a viable tool to address the mentioned problems. It links the insights from the different domains of marketing, design and production to a coherent view on how variation is propagated and what impact it has. It is assumed that Robust Design can capitalize on that information especially with respect to robustness evaluation and creating a comprehensive functional overview of the product.

The aim of this study was therefore to develop a tool extending and operationalizing the VMF. A holistic approach was conducted to integrate and unify all structural and functional information generated during product development and production. The study at hand is fourfold and was conducted as follows:

(1) To get an idea about the severity of the mentioned problems in industry, a survey was conducted among product development and production professionals (section 2).
(2) The VMF was then further developed and extended to address the encountered problems (section 3).
(3) The tool was successively presented and a trial use conducted at a Robust Design workshop with practitioners from industry (section 4.1).
(4) Following the workshop, an in-depth case study at a medical company was run to test the value and applicability of the tool (section 4.2).

2 Survey and state of the art

Although the problem of variation is not new and there are various academic and industrial proposed strategies and tools, a lot of evidence for symptoms of problems in relation to variation can be found (Ebro 2015). Preceding the Robust Day 2016 held at the Technical University of Denmark a survey was conducted among the delegates, Robust Design practitioners from Product Development, Production and Management, asking to rate the severity of Robust Design related issues in the development and production of their companies. The questionnaire included the following statements that were hypothesized to negatively influence the efficient application of Robust Design as well as variation management and needed to be rated from 1 "Strongly disagree" to 5 "Strongly agree" on a Likert-type scale:

(1) Silo thinking hinders the ability of our organization to deliver product quality.

(2) Unquantified decision making is a major cost/opportunity-cost for our organization.

(3) Uncertainty of impact of design/production change/variation is a major cost/opportunity-cost for our organization.

(4) Non-optimal designs and trade-offs is a major cost / opportunity-cost for our organization.

42 responses were collected. The results of the survey are shown in Figure **1** and, although the sample of participants is not representative, give an indication that the hypothesized issues are indeed present in practice. Between 55 and 70% of the delegates "agreed" or "strongly agreed" with the statements.

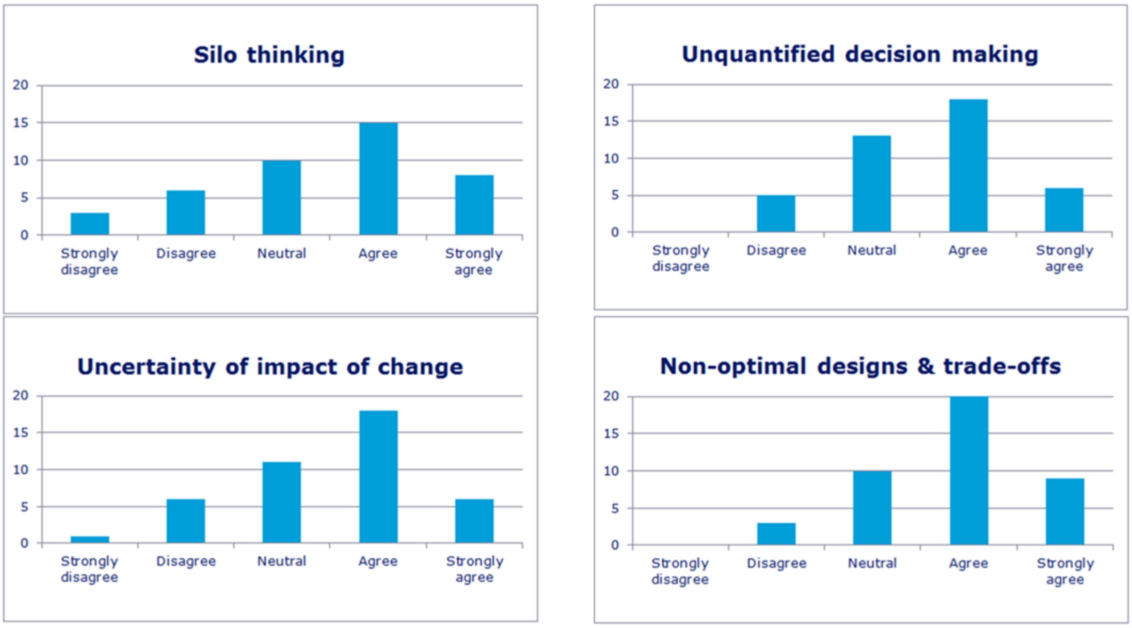


Figure 1. Results from a survey regarding Robust Design related issues in product development and production

There are various tools and strategies in the literature which aim at an efficient variation management to address aforementioned problems. In the following, the state of the art will briefly be discussed with focus on their ability to support Robust Design throughout the development from the initial concept to production including type I but especially also type II Robust Design, meaning robustness against noise factors and variation in design parameters respectively (Allen et al. 2006). Specifically, the existing tools and frameworks were evaluated against, whether they…

(1) …have a holistic approach to include marketing and production considerations to Robust Design to address issues related to silo-thinking.

(2) …support a Key Characteristic approach to ensure applicability.

(3) …support various fidelities of Transfer Function (TF) models including qualitative as well as linear and non-linear quantitative models to support type II Robust Design.

(4) …exploit structural (complexity related) information to capture interaction related robustness issues arising from coupling (Suh 2001) as well as trade-offs and contradictions (Göhler, Frey, and Howard 2016; Göhler and Howard 2015) to support Robust Design from conceptual design onwards.

(5) …enable and supply metrics like sensitivities, functional variance, size of design space, and yield rates (Göhler, Eifler, and Howard 2016; Saltelli et al. 2008) to monitor and prioritize efforts and make quantified, objective decision for metric-driven Robust Design.

Nowadays, PLM (product lifecycle management) systems have the capabilities to seamlessly integrate simulation software to holistically evaluate complex (multi-function) designs. Especially for tolerance allocation and analysis in the detailed design stage, many tools for variation simulation and analysis (VSA) as well as robustness and production optimization exist (see for example (Beyer and Sendhoff 2007; Etienne et al. 2008; Söderberg, Lindkvist, and Dahlström 2006)). However, there are several issues: firstly, mature models are necessary which are not available in earlier design stages. Secondly, there is no Key Characteristics (KC) approach reducing the complexity and complicatedness of the task. And thirdly, structural information to support Robust Design on the conceptual design stage is not utilized.

In the Variation Risk Management (VRM) methodology by Thornton (2004), the complexity of the problem is addressed by identifying Key Characteristics (KC) and by the utilization of surrogate (linear) models as well as decomposition of the variation problem from product KCs all the way to production process KCs. Dantan et al. (2008) pursue a similar approach to variation management (VM) where a KC flowdown is combined with a condition flowdown to capture causalities and conditions on the characteristics. Both, Thornton and Dantan, have a strong focus on geometry and manufacturability with Robust Design being only a side aspect and the customer domain neglected entirely.

The House of Quality (HoQ) within the Quality Function Deployment (QFD) methodology is a method to qualitatively map a product from the customer through the engineering to the production domain (Hauser and Clausing 1988). It conveys the customer attributes by relating those to engineering characteristics and further to parts characteristics, key process operations and production requirements. The relations of the "whats" to the "hows" are captured in matrix form similar to multiple domain matrices (MDMs) (Maurer 2007). The main issue with the House of Quality with respect to robustness analysis and variation management is that quantitative models are not included. Furthermore, there is no differentiation between variation sensitive and insensitive parameters.

Another framework, Axiomatic Design (AD), builds upon two design axioms to foster robustness (Suh 2001): the independence axiom (Axiom 1) prescribing to un- or decouple the design and the Information axiom (Axiom 2) which seeks for an optimized adequate robust design for the highest probability of conformance. Axiomatic Design is a framework to support system design top-down (Suh 1998) with a meaningful decomposition into four domains, the customer, functional, physical and process domain. The mapping between the domains is done via design matrices, which are stiffness matrices comprising the linearized sensitivities. As the HoQ, Axiomatic Design does not distinguish between variation sensitive and insensitive parameters.

Recently, Howard et al. proposed the Variation Management Framework (VMF), a visualization and education tool (2017). It illustratively presents how variation maps through the domains of marketing, design and production and supports a holistic approach to variation management and Robust Design. However, the VMF considers only one-dimensional mappings of one Market Parameter to one Functional Parameter to one Design Parameter to one Process Parameter limiting the practical use of the tool to educational purposes.

In summary, there exist various useful tools and frameworks for variation management. However, none of them support Robust Design in a holistic and metric-driven way from the initial to final design including structural and functional information. Problematic is also the applicability for complex products of tools which do not use a KC approach. The capabilities of the current methods and tools with respect to the criteria laid out earlier in this section are summarized in Table 1.

Table 1. Summary of capabilities of state of the art variation management tools

		PLM / Robustness optimization	VRM	VM by Dantan	HoQ	AD	VMF
1.	Holistic	✓			✓	✓	✓
2.	System decomposition to KCs		✓	✓			✓
3.	Various fidelities of TF models			✓			
4.	Exploitation of structural information				✓	✓	
5.	Robust Design metrics	✓				✓	✓

3 Development of Support tool

In this section, the development of the support tool is described. Taking a point of departure from the Variation Management Framework (VMF) by Howard et al. (2017)

which already reflects and incorporates many of the elements listed in Table 1, the VMF Tool is developed addressing the 5 requirements one by one. A focus is also put on the applicability and ability for operationalization of the tool for complex products in industry, i.e. scalability and the option for implementation in a software solution.

3.1 A holistic approach to Robust Design

In the Variation Management Framework (Howard et al. 2017), a holistic view on variation is taken. In its graphical representation, it differentiates between three so-called quadrants of variation management: the marketing, design and production quadrant. In those, the four product domains customer, functional, physical and process domain are linked, in particular the characteristics Market Parameters (MP)[1] (***Footnote[1] Termed CS (Customer Satisfaction) in previous articles – adopted from Axiomatic Design***), Functional Parameters (FP), Design Parameters (DP) and Process Parameters (PP) respectively (Figure **2**). Robust Design as the main approach for variation management in the design quadrant is the means to ensure that physical variation in production is not perceived by the customers in the market due to a compromised functionality. The VMF enables a cross-department and cross-functional collaboration for Robust Design and variation management addressing the experienced issues with silo-thinking.

To achieve this holistic approach to variation management and Robust Design in particular the VMF Tool needs to be object/element-based and structured by the four product domains.

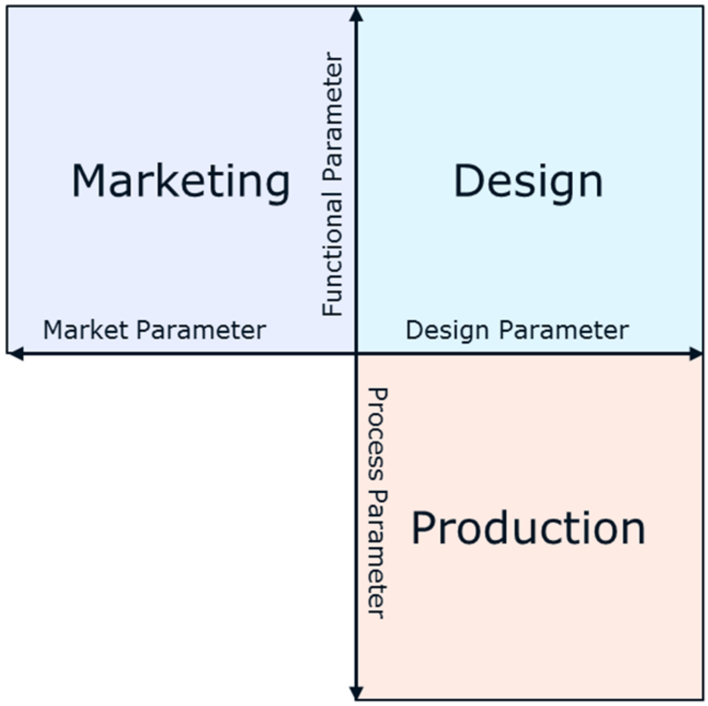


Figure 2. Quadrants of the VMF

3.2 Key Characteristics Approach

To ensure applicability in real-world development projects of complex products a Key Characteristics (KC) approach is inevitable. Due to the sheer number of Design and Process parameters, variation management including modelling and controlling of the parameters needs to be limited to the most influential ones. Two criteria are decisive for the identification of a KC. Firstly, variation of a parameter needs to have a significant impact on the product and secondly, it needs to be likely that the parameter experiences substantial variation (Thornton 2004).

The KC approach has a lesser influence on the VMF Tool itself but on the process and way it is used. However, the VMF Tool needs to support the capturing of KCs but also a further analysis and differentiation among the KCs for ranking and prioritization purposes once they are captured in the tool.

3.3 Support of various fidelities of Transfer Functions

The VMF Tool is supposed to support Robust Design and variation management throughout the design process from conceptual to detailed design and production ramp-up. It is acknowledged that information about the design becomes available in different forms, at different points in time and with different levels of uncertainty. The assumption that quantitative models are available for all functions is not realistic. Throughout the design process information arrives with low to high fidelity. In early design stages, it is often possible to perform a KC flowdown based on subject matter expertise and experience to identify influencing parameters and in some instances to qualitatively evaluate the influence of one characteristic to another. In later phases, first quantitative, oftentimes simplified linear models are derived enabling the estimation of sensitivities and variation propagation characteristics, i.e. whether variation is damped or amplified. In the detailed design stage, more quantitative information and sophisticated models become available from 3D numerical simulations like FEA or CFD and experiments on prototypes. Figure **3** provides an example of the different levels of model fidelity with the dependence of a Functional Parameter (FP1) on a Design Parameter (DP1). Starting from a qualitative information that two characteristics are related (1) and then how they are related (2) to the quantitative description of the relation with FP1's sensitivity to DP1 being "-5 Units per unit change" for a linear model (3) and "-10 Units per unit change" for the non-linear model (at $DP_1 = 1$) (4).

The VMF Tool needs to reflect the nature of the data and the way it is utilized and applied. A viable solution for the tool is to capture besides the product characteristics themselves as discussed in section 3.1 also the relations among them.

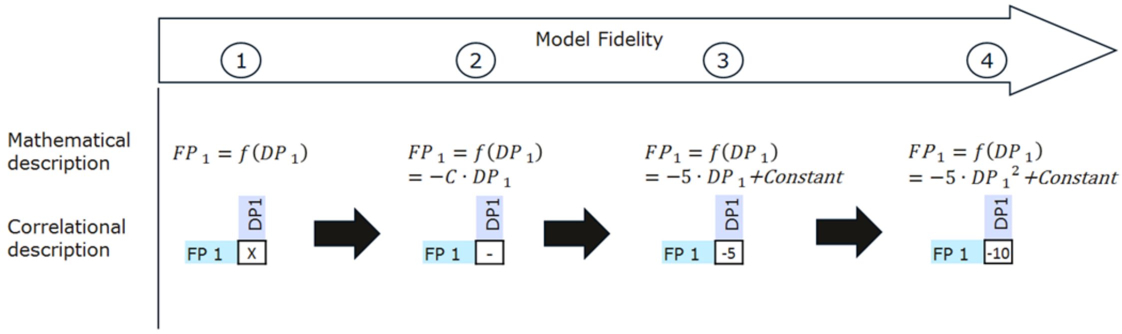


Figure 3. Different levels of Transfer Function model fidelity

3.4 Exploitation of structural information

Research by Suh (2001) and Göhler et al. (2016; 2015) found that the structural complexity of a product has an impact on its robustness. Following Suh's Axiomatic Design, coupling should be avoided to ensure an optimal and robust design. It can be quantitatively shown that in the case of nominal-the-best requirements the degree of coupling has a negative influence on the robustness of the design. Göhler et al. showed that coupling information can further be evaluated and it can be differentiated between positive and contradicting couplings. In the case of smaller/larger-the-better requirements, contradictions reduce robustness whereas positive couplings do not have an adverse effect. Since couplings and contradictions can often already be evaluated on conceptual level, this structural information can be used in early design stages before quantitative models become available. Functional coupling and contradiction can reveal potentially critical functions, parameters and trade-offs between them that need further investigation. Visual representation of the couplings in matrix- or graph-form can support engineers to identify those.

Figure **4** shows a multiple-domain matrix (MDM) of an example design solution containing 5 functions and 15 design parameters. The matrix is populated with simple binary and qualitative relational data as discussed in the preceding section. Function 4 is coupled with functions 1, 2 and 3. However, the coupling with function 3 is a positive one with no adverse effect. With this information the coupling between functions 1, 2 and 4 through the DPs 5,6 and 11 can be flagged and the awareness gained by this analysis helps to prioritize further design and analysis tasks. Anticipating functional design flaws is difficult. “Easy” flaws can be found by review and analysis. However, detecting complex interaction effects that create issues are often not found until testing. A support tool like the VMF Tool needs to provide a functional overview for example in matrix-form as displayed in Figure **4**.

	F1	F2	F3	F4	F5	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	DP11	DP12	DP13	DP14	DP15
Function 1				X			X	X	X	X	X									
Function 2				X		X										X				
Function 3				+									+	+						
Function 4	X	X	+							X	X	X	+	+	X	X	X			
Function 5																		X	X	X

Figure 4. Example MDM to illustrate couplings

3.5 Support of analyses and algorithms to generate robustness metrics

The quantification of sensitivities and robustness of concepts and design solutions has a high importance for the development process of a product to monitor, prioritize and decide on objective and quantified grounds (Göhler, Ebro, and Howard 2016). A maxim oftentimes brought forward in quality engineering is that “You can only improve what you can measure” (Fowlkes and Creveling 1995). ”Unquantified decision making” was identified as a major issue in the survey presented in section 2. Ideally, all decisions should be as metric-driven as possible. To derive robustness metrics like for example discussed by Göhler et al. (2016), quantitative models as well as certain analysis capabilities like Monte-Carlo-Analysis, sensitivity analysis and techniques for ANOVA and HDMR (High dimensional model representation) need to be available for the VMF

Tool.

3.6 Structure of the VMF Tool

Through the preceding sections 3.1 to 3.5 the VMF Tool was developed based on the requirements and functionality discussed in section 2. Figure **5** shows the resulting structure of the VMF Tool to capture and unify the patchwork of different insights about the product and provide a platform for analyses and a functional overview to support Robust Design and variation management. All information about the design is gathered systematically and stored centrally in the “VMF Database”. This is done through the registration of relations and Transfer Functions featuring the different levels of fidelity in the form:

$$y = f(x_1, x_2, \dots, x_n)$$

Where y is the dependent element (for example a function F1) and xi are the influencing elements (for example DPs). Analogous to PLM systems, which organize structural information, i.e. drawing, assemblies, manufacturing, and its documentation, this database captures functional information and offers system-wide robustness, sensitivity and change or variation propagation analyses. Different visualizations including matrix and graph-based visualizations are available to attain an overview and help to guide design change and improvements. The ability for a scalable software implementation is essential to address the complexity of real-world products and systems (Dantan et al. 2008). Analogous to PLM systems, a certain collaborative and multi-user capability should be envisaged to make the tool applicable.

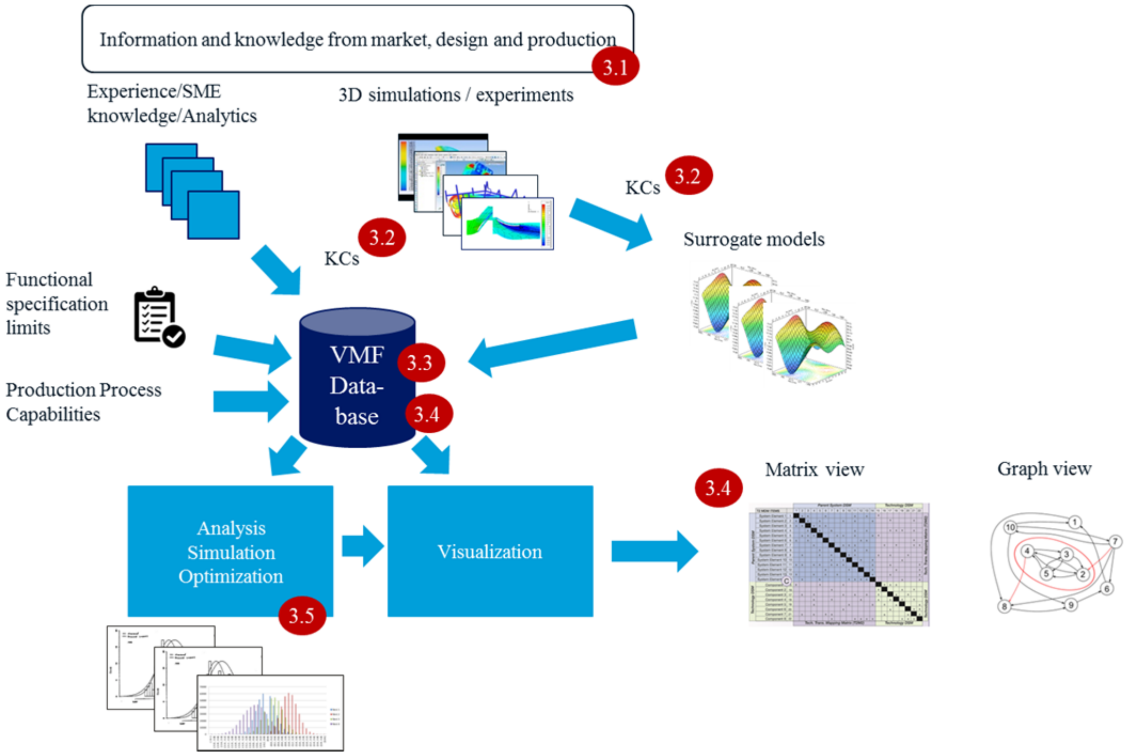


Figure 5. Structure of the VMF Tool

In practice, it was experienced that the decomposition from Functional Parameter to Design Parameters in one step is in many cases not practical. An example is an abstract Functional Parameter like the top speed of a car. The decomposition to the DPs in one step is in that case not very sensible. To ensure applicability for complex products a further decomposition of the functions to so-called sub-functional parameters is therefore utilized (Göhler, Husung, and Howard 2016).

4 Case Studies

Two different case studies were run to test and evaluate the tool. In particular, the goodness and success of the VMF Tool was evaluated against its ability to address the issues discussed in the survey. The first study aimed to broadly evaluate the utility of the VMF tool in a workshop getting feedback from multiple participants serving very different products and systems. The second case was to conduct an in-depth study of a product in order to identify exactly where and how the VMF tool would be used and whether it adds value to the product life cycle.

4.1 Trial application in a workshop situation

A first test of the VMF tool proposed in this contribution was conducted in a workshop at the Robust Design Day 2016. Case product was the Vaavud wind reader Sleipnir (Figure **6**). The Sleipnir consists of 6 parts with numerous design as well as process parameters and was chosen as a simple case adequate for a 2h workshop trial of the VMF Tool. Five tasks were completed related to scenarios in detailed design and production. Figure 6 shows the trial version of the tool for the Vaavud Sleipnir wind reader. The details of the workshop and the case are publically available under http://pd-symposium.org/RDD.php.

After the completion of the workshop, the participants were asked in a survey, whether the VMF Tool would provide a solution to address the issues related to Robust Design and variation management that were judged relevant in the pre-survey. The same 5 level Likert-type scale was used as in the pre-survey. 40 responses were returned with the results shown in Figure **7**. On average 78% of the participants "agreed" or "strongly agreed" that the proposed VMF tool provides a solution to address the encountered problems. Although this is a subjective evaluation conducted by a non-representative group of industry delegates, the results give an indication about the value and potential of the tool. The survey also included a feedback section, which showed that the main concerns about the tool were regarding the applicability in complex products and the efficiency of the data entry. However, there was generally positive feedback and encouragement for further development of the tool.

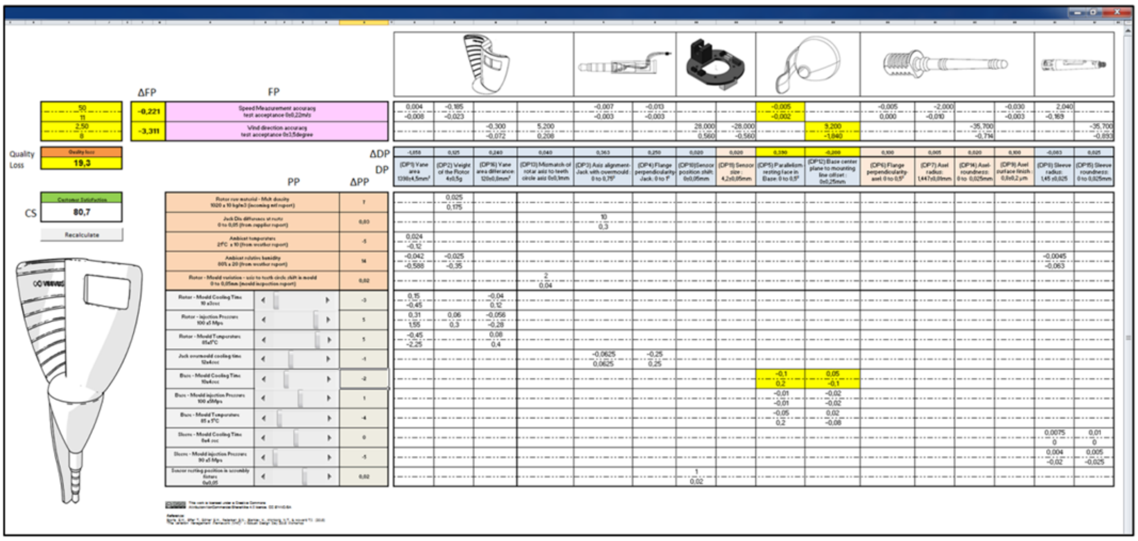


Figure 6. Trial version of the VMF Tool from the Vaavud Sleipnir workshop case study (Boorla et al. 2016)

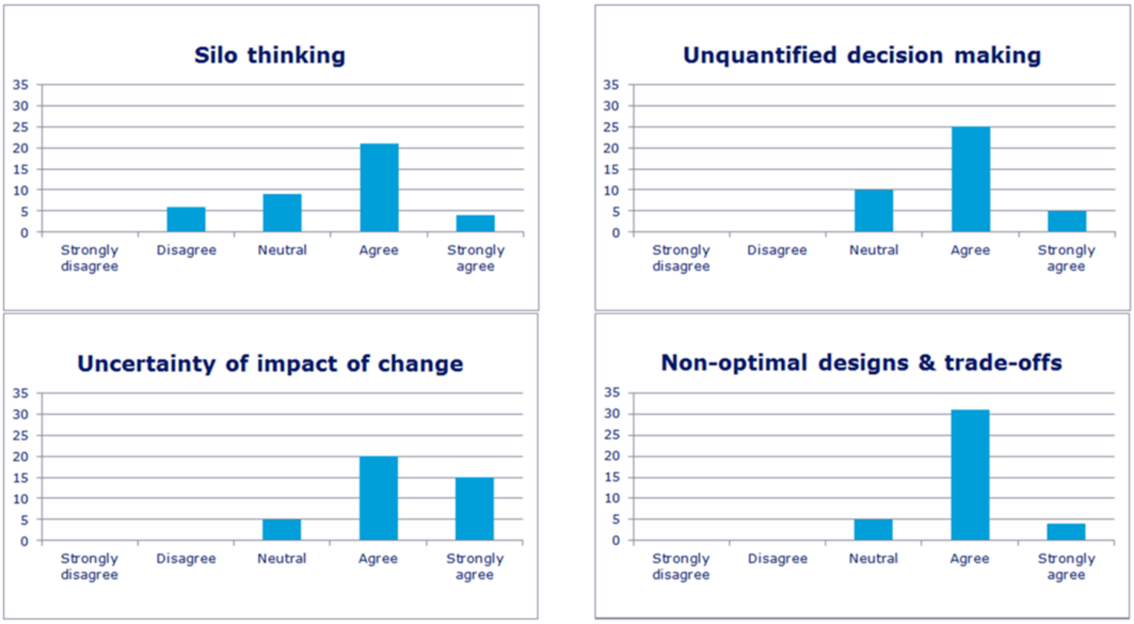


Figure 7. Results from a survey regarding the suitability of the VMF to solve Robust Design related problems in product development and production

4.2 In-depth Product Case study

Following the workshop, the VMF tool was further developed improving the data entry and tested in an in-depth product case study in the medical industry to evaluate its value and applicability.

The product in the centre of the case study was a medical device measuring parameters relevant to a patient's well-being and providing healthcare professionals with important information for diagnosis and treatment. More specifically, in this case study, the design of a complex sensor comprising of several sub-components was investigated.

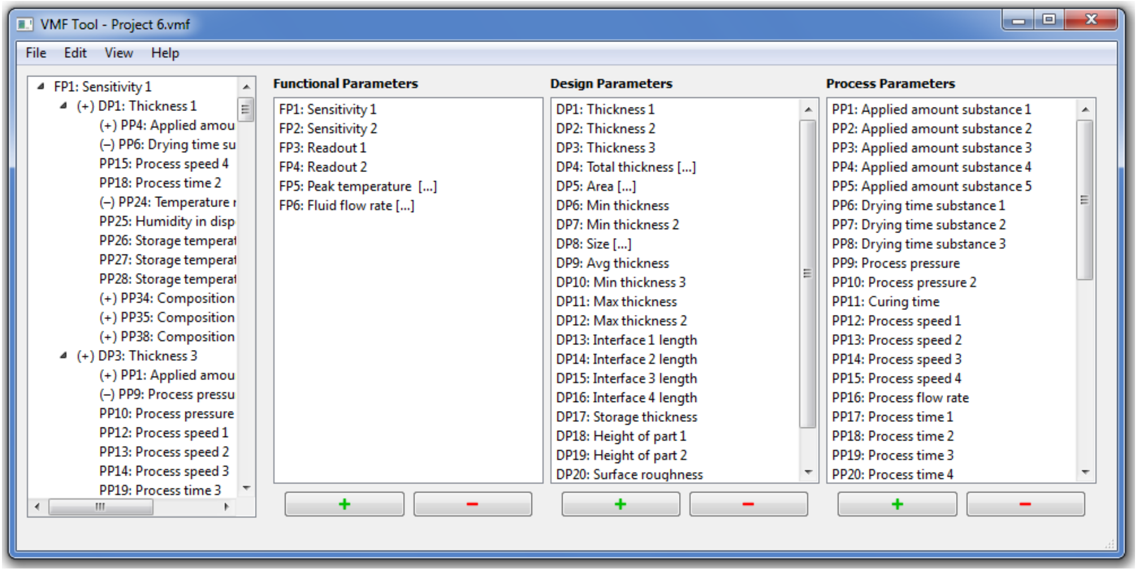


Figure 8. Main window with reduced and anonymized data

The main functional requirements are concerned with the reliable and accurate detection of an analyte. Typical design and process parameters are chemical and mechanical properties of the sensor as well as drying time respectively. In total, 25 functional parameters and more than 400 design and process parameters were identified and mapped. From interviews and practice it was clear that although tests are conducted to understand the relationships between functions and design / process parameters, it was difficult to maintain a comprehensive overview. While the data was available in digital formats, it took the external researchers several weeks to gain sufficient insight and a basic overview. An improved centralization of the data may be seen as a way of reducing data compilation overhead for design iterations, in turn making such iterations more appealing. Also the communication across departments, e.g. Design and Production, regarding function understanding and variation would likely benefit from a centralized support tool. These challenges perceived by the external researchers during the study can be interpreted as related to the issues expressed in the survey conducted at the Robust Design Day 2016.

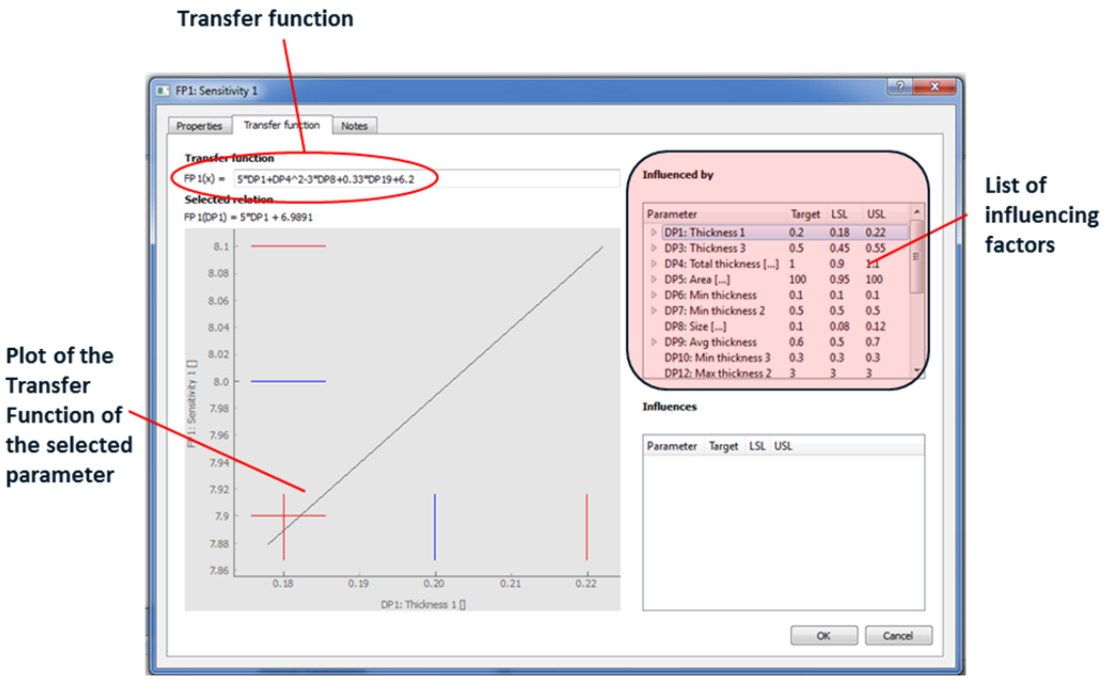
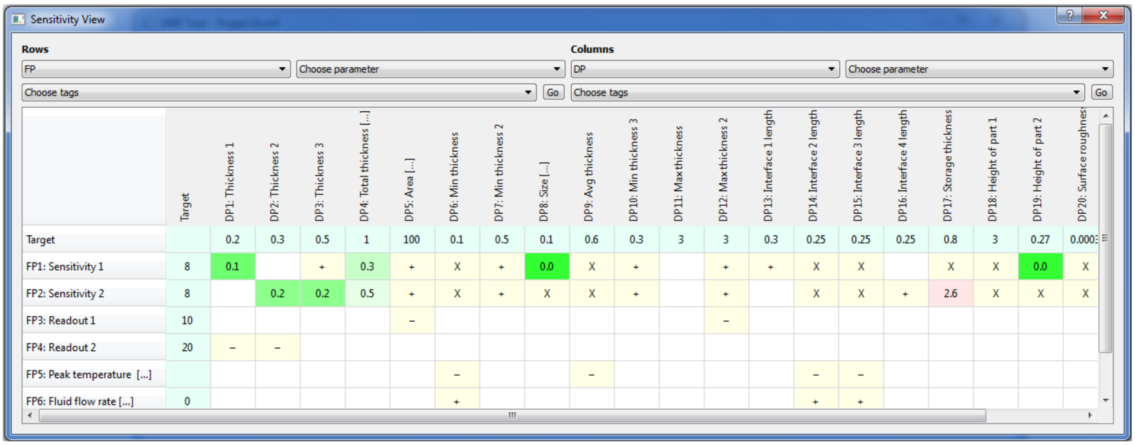


Figure 9. VMF Tool data entry window (data changed for confidentiality reasons)

Figure **8** shows a part of the product mapping in the main window of the VMF tool. Note that “market parameters” could be omitted in this study due to the fact that they were identical to the functional parameters for the sensor driven by regulations. The data was modified to disguise any propriety data. Different sources across the organization were utilized to gather the data including design reports, process specification reports, test and validation reports as well as data from production and subject matter experts. The strength of the VMF tool is that it integrates the different fidelities of information. Where significant correlations were found, the Transfer Function was included as shown in the data entry window displayed in Figure **9**. The product mapping gave a functional overview and insights to the sensor increasing the awareness to change and variation propagation and influences. Couplings and contradictions potentially leading to restricting trade-offs and robustness issues could be identified. Furthermore, where significant correlation was found, the sensitivities of parameters to functions were presented in the VMF Tool. Figure **10** shows the "Sensitivity view" in the VMF Tool marking binary relational information with an "X", positive and negative influences with a "+" and a "-" respectively and displaying the Nominal-range sensitivity (NRS) (Göhler, Eifler, and Howard 2016) as relative measure for the propagation of variation (NRS < 1 = damping of variation; NRS > 1 = amplifying of variation).



	Target	DP1: Thickness 1	DP2: Thickness 2	DP3: Thickness 3	DP4: Total thickness [...]	DP5: Area [...]	DP6: Min thickness	DP7: Min thickness 2	DP8: Size [...]	DP9: Avg thickness	DP10: Min thickness 3	DP11: Maxthickness	DP12: Maxthickness 2	DP13: Interface 1 length	DP14: Interface 2 length	DP15: Interface 3 length	DP16: Interface 4 length	DP17: Storage thickness	DP18: Height of part 1	DP19: Height of part 2	DP20: Surface roughnes
Target		0.2	0.3	0.5	1	100	0.1	0.5	0.1	0.6	0.3	3	3	0.3	0.25	0.25	0.25	0.8	3	0.27	0.0003
FP1: Sensitivity 1	8	0.1		+	0.3	+	X	+	0.0	X	+		+	+	X	X		X	X	0.0	X
FP2: Sensitivity 2	8		0.2	0.2	0.5	+	X	+	X	X	+		+		X	X	+	2.6	X	X	X
FP3: Readout 1	10					–							–								
FP4: Readout 2	20	–	–																		
FP5: Peak temperature [...]							–			–					–	–					
FP6: Fluid flow rate [...]	0						+								+	+					

Figure 10. Sensitivity view (data changed for confidentiality reasons)

Once all the information was gathered it was important that the VMF Tool and its representation were easily interpreted by those related to the project. To test the merit and applicability of the tool to handle complexity and a high number of parameters, an experiment with 4 employees from the case company was set up. The task was to identify the influencing parameters to a function from a patchwork of analysis results conducted previously. The complexity of the task, i.e. the number of functions and parameters, was increased in 3 steps ranging from 15 to 60 parameters, which is only a subset of the data and was chosen due to time and availability constraints of the participants of the experiment. Although a small sample size, the test showed that with increasing complexity the tool improved the speed and accuracy (completeness) of solving the task compared to the common approach using spreadsheets.

5 Conclusion

In this contribution, a tool was presented to support variation management and Robust Design from the conceptual design stage onwards throughout the development and production. It addresses the identified shortcomings of current tools failing to capitalize on both structural and functional information in a holistic and comprehensive manner whilst providing a KC-driven and scalable solution to support the development of complex products. Based on the Variation Management Framework (VMF) (Howard et al. 2017), the VMF Tool was developed utilizing an object-based relational database featuring analyses and representations of the data to increase the functional understanding of complex products and to evaluate the robustness of its design. The strengths of the tool lie within the integration and conflation of the available information to all members of the development team. With the scalable architecture of the tool and an input interface that enables a piecewise input of data driven by functional decomposition, the practical applicability is ensured.

The VMF tool was successfully tested in a trial application in a workshop with Robust Design practitioners and in an in-depth product case study. The increase in functional understanding including couplings, contradictions and the metric-driven approach utilizing sensitivities as well as other robustness metrics enabled the users of the VMF Tool to efficiently and holistically address problems related to Robust Design and variation management such as understanding of variation propagation and non-optimal designs and trade-offs. Positive feedback from the workshop participants as well as the participants from the case company was also given regarding the capabilities of the VMF tool to support the communication between departments related to variation and sensitivity data.

A challenge was still seen in the entry of the data as well as the speed and efforts of keeping it up to date. It is anticipated that the total amount of analyses and efforts remains the same compared to current practice with the difference that necessary analyses can be identified and conducted earlier. Filling, maintaining and keeping the data included in the tool up to date is a challenge that has also been experienced and overcome in PLM/PDM systems. The main focus area for further research lies therefore in the process of using the tool in product development. Furthermore, additional features for the tool to capture the uncertainty and sources of information as well as the inclusion of the monetary dimension as also discussed by Etienne et al. (2016) and Mirdamadi et al. (2013) to evaluate costs and benefits of certain activities and actions is planned for the future development.

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